Reserve Bank of India

OCCASIONAL PAPERS

Vol.43 - No. 1: 2022
ISSN 0972 - 7493

Carbon Dioxide Emissions from India's Manufacturing Sector: A Decomposition Analysis
Shashi Kant, Madhuresh Kumar, Shahbaaz Khan and Somnath Sharma

Sensitivity of Pension Liabilities of Banks to Various Actuarial Assumptions
R. K. Sinha

Do Bank Mergers Improve Efficiency? The Indian Experience
Snehal S. Herwadkar, Shubham Gupta and Vaishnavi Chavan

Behaviour of Credit, Investment and Business Cycles: The Indian Experience
Sujeesh Kumar, Pawan Kumar and Anand Prakash

Book Reviews

RESERVE BANK OF INDIA

EDITORIAL TEAM

VOLUME 43 - NO.1 2022

The objective of the Reserve Bank of India Occasional Papers is to publish high quality research produced by the staff of the Reserve Bank of India on a broad array of issues of interest to a large audience including academics and policy makers. The papers selected for publications are subject to intense review by internal and external referees. The views expressed in the articles, notes and reviews published in this journal are those of the authors and do not reflect the views of the Editorial Committee or of the Reserve Bank of India. Moreover, the responsibility for the accuracy of statements contained in the contributions rests with the author(s).

The print copy is available for sale (Monday to Friday) at the Sales Section, Division of Reports and Knowledge Dissemination, Department of Economic and Policy Research, Reserve Bank of India, Amar Building, Ground Floor, Sir P. M. Road, Fort, P.B. No.1036, Mumbai - 400 001. The contact no. of Sales Section is 022-2260 3000 Extn.: 4002, email: spsdepr@rbi.org.in.

Price : Inland : ₹ 200
₹ 250 (inclusive of postage)
Foreign : US $ 18 (inclusive of air mail courier charges)

All other correspondence may be addressed to the Editorial Team, Reserve Bank of India Occasional Papers, Department of Economic and Policy Research, Reserve Bank of India, Post Box No. 1036, Mumbai-400 001;
email: occasionalpapers@rbi.org.in

RESERVE BANK OF INDIA

OCCASIONAL PAPERS

RESERVE BANK OF INDIA

RESERVE BANK OF INDIA

OCCASIONAL PAPERS

VOL. 43, NO. 1 **2022**

Articles		Author	Page
Carbon Dioxide Emissions from India's Manufacturing Sector: A Decomposition Analysis	:	*Shashi Kant, Madhuresh Kumar, Shahbaaz Khan and Somnath Sharma*	1
Sensitivity of Pension Liabilities of Banks to Various Actuarial Assumptions	:	*R. K. Sinha*	29
Do Bank Mergers Improve Efficiency? The Indian Experience	:	*Snehal S. Herwadkar, Shubham Gupta and Vaishnavi Chavan*	71
Behaviour of Credit, Investment and Business Cycles: The Indian Experience	:	*Sujeesh Kumar, Pawan Kumar and Anand Prakash*	119
Book Reviews			
In Defense of Public Debt by Barry Eichengreen, Asmaa El-Ganainy, Rui Esteves, and Kris James Mitchener	:	*Akash Kovuri*	155
Geopolitics, Supply Chains, and International Relations in East Asia Edited by Etel Solingen	:	*Rashika Arora*	161
Chain Reaction: How Blockchain Will Transform the Developing World by Paul Domjan, Gavin Serkin, Brandon Thomas and John Toshack	:	*Anshu Kumari*	167

Reserve Bank of India Occasional Papers

Vol. 43, No. 1: 2022

Carbon Dioxide Emissions from India's Manufacturing Sector: A Decomposition Analysis

Shashi Kant, Madhuresh Kumar, Shahbaaz Khan and Somnath Sharma*

Received on: March 30, 2022
Accepted on: June 22, 2022

This paper decomposes the total carbon dioxide (CO_2) emissions in the manufacturing sector of India during the period 2009-10 to 2017-18 into factors, such as output growth, structural changes, energy intensity changes and fuel mix changes using the Logarithmic Mean Divisia Index (LMDI) method. It finds that while a reduction in energy intensity and structural changes in manufacturing activities have led to an overall reduction in CO_2 emissions, growth in output and changing fuel mix have contributed to higher emissions. The dominance of coal and coal-powered electricity in fuel consumption remains the most significant cause of CO_2 emissions in India, warranting a sustained policy thrust on renewable sources of energy for faster green transition.

JEL Classification: Q41, Q54, O14, L60.

Keywords: Decomposition, carbon emissions, CO_2 emissions, energy intensity, climate change, LMDI.

---

* Shashi Kant (skant@rbi.org.in) and Somnath Sharma (somnathsharma@rbi.org.in) are Assistant Advisers; Madhuresh Kumar (madhureshkumar@rbi.org.in) and Shahbaaz Khan (shahbaazkhan@rbi.org.in) are Managers, Department of Economic and Policy Research, Reserve Bank of India. Useful comments from discussant Paritosh Jha, anonymous external referee, Principal Adviser Deba Prasad Rath, Executive Director Sitikantha Pattanaik, and other participants of the DEPR Study Circle are gratefully acknowledged.

The authors also thank Akanksha Handa, Manager, Department of Economic and Policy Research for her valuable suggestions.The views and opinions expressed in this paper are those of the authors and do not necessarily represent those of the institution to which they belong.

Introduction

The manufacturing sector is one of the key drivers of India's economic growth, contributing around 15 per cent to India's Gross Value Added (GVA). It is also the second-largest contributor to carbon dioxide (CO_2) emissions (25 per cent) after electricity generation (Biswas *et al*., 2019; Gupta *et al*., 2019). This sector is by nature energy-intensive resulting in large emissions of greenhouse gases and is also sensitive to technological change. These characteristics of the manufacturing sector may lead to changes in its CO_2 emissions over time through changes in input requirements and improvements in energy efficiency.

The annual Conference of Parties (COP) on Climate Change, popularly known as COP26, held in Glasgow from October 31 to November 13, 2021, called on all the stakeholder countries for a collective action towards a systematic reduction in greenhouse gases emissions. COP26 sought commitments from every country to cut CO_2 emissions, with an end objective of becoming net-zero in a targeted timeframe. Such intended decoupling between economic growth and CO_2 emissions is possible if significant steps are taken in the manufacturing sector towards the reduction of CO_2 emissions. The first step towards this is understanding the major factors contributing to CO_2 emissions in the manufacturing sector.

In this paper, we decompose the increase in CO_2 emissions from India's manufacturing sector as a result of a rise in output levels, changes in the fuel mix, improvements in energy efficiency in the manufacturing processes and variations in the composition of the overall manufacturing output. As technologies improve over time, manufacturing units adopt new ways of production to save costs and increase efficiency. The overall compositional structure of the manufacturing industry also changes with time, altering the CO_2 emissions from the manufacturing industry. Illustratively, if the composition of the manufacturing sector changes such that the share of industries emitting less CO_2 increases, the overall CO_2 emissions from the manufacturing sector may decline. In this paper, we also analyse the key patterns in fuel usage across various types of industries classified according to their sizes (micro, small, medium and large) to see if smaller industries produce the same amount of output with lesser emissions which may have wide implications for policy planning. The novelty of this paper lies in its use of granular plant-level fuel consumption data published as part of the Annual Survey of Industries (ASI), which has hitherto remained underutilised for research on green transition.

We use the logarithmic mean divisia index (LMDI) decomposition technique that has been extensively used by researchers for the decomposition of CO_2 emissions. We find that despite being carbon intensive in nature, the manufacturing sector is undergoing a faster green transition than the overall economy. Increasing output in the manufacturing sector is the biggest contributor to emissions. The contribution of the manufacturing sector to emissions is explained by the use of a more carbon-intensive fuel mix, but this effect is offset by energy efficiencies in manufacturing processes and a structural shift to cleaner industries.

The rest of the paper is structured as follows. Section II reviews various studies that have used several decomposition techniques. Section III describes the LMDI methodology. Data processing is discussed in Section IV alongside some stylised facts using ASI data. Results of the decomposition analysis are discussed in Section V. Section VI concludes the paper.

Section II
Literature Review

Energy identities provide the basis to establish a quantitative relationship between CO_2 emissions and, their contributing factors. Globally, studies have mainly used two techniques to decompose the change in CO_2 emissions over time – structural decomposition analysis (SDA) and index decomposition analysis (IDA). Of the two methods, SDA is more rigorous and exhaustive based on input-output tables. The SDA model has been widely used to distinguish the direct and indirect socio-economic effects from intermediate production and final consumption perspectives (Wang and Wang, 2015). The limiting factor in its use for CO_2 emissions decomposition is the availability of input data for fuels of various types, which are clubbed together as one entity in many cases.

On the other hand, index decomposition analysis (IDA) has been extensively used as an analytical framework by researchers to quantify the impact of change in output, structure, and energy intensity of various economic activities on energy use trends. Since the early 1990s, IDA has been extended to CO_2 emissions by including two additional variables, fuel mix and emission coefficient effects. The IDA methods mainly include the Laspeyres and the Divisia index decomposition methods (Qu, 2020).

It may be noted that the Laspeyres index decomposition does not allow for a complete decomposition and leaves unexplained residual terms. However, the refined Laspeyres index methods *viz.*, Fisher ideal index, Shapley and Sun decomposition methods allow for a complete decomposition and the final results obtained are more accurate. Logarithmic mean divisia index (LMDI) and arithmetic mean divisia index (AMDI) are the prominent methods belonging to the divisia index family. Ang (2004) lists four tests in index number theory to determine the desirability of a decomposition method, namely – factor-reversal, time-reversal, proportionality and aggregation tests.[1] The factor reversal test is most important while choosing the appropriate method. Table 1 exhibits the properties of various decomposition methods.

Fischer, Shapley/Sun and LMDI satisfy the factor reversibility test. However, LMDI has been used in this paper because of several reasons as enumerated in Ang (2004). The multiplicative LMDI also possesses the additive property in the log form. Theoretically, the results given by multiplicative decomposition and additive decomposition should be relatable. In addition, a major difference between the LMDI and the methods linked to the Laspeyres index approach is the ease of formulation. The number of terms in the formulation of the Shapley/Sun method grows manifold with the increase in the number of factors making its implementation difficult. As a result, LMDI methods are more popular in decomposition when the number of factors exceeds three (Ang, 2004). Also, there are no negative values in the dataset making LMDI method a suitable choice for decomposition.

[1] Factor reversal test means a complete decomposition and leaves no unexplained residue. Time reversal test denotes that if the time period is reversed the decomposition would yield reciprocal results. Proportionality test means that if the value of determinants changes by λ, then the index value is λ. Consistency in aggregation allows the results obtained for sub-groups to be aggregated to a higher aggregation level in a consistent manner (Vartia, 1976; Balk, 1996; Ang and Liu, 2001). The zero-value robust (Ang and Choi, 1997) and the negative-value robust test (Chung and Rhee, 2001) are additional two tests to help determine the suitable decomposition method.

Table 1: Properties of IDA Methods

IDA Method	Factor Reversal Test	Time Reversal Test	Proportionality Test	Aggregation Test	Zero Value Robust	Negative Value Robust
Laspeyres	No	No	Yes	Yes	Yes	Yes
Modified Fisher Decomposition	Yes	Yes	Yes	No	Yes	Yes
Shapley and Sun	Yes	Yes	Yes	Yes	Yes	Yes
AMDI	No	Yes	Yes	No	No	No
LMDI	Yes	Yes	No	Yes	Yes	No

Note: The LMDI used here refers to the logarithmic mean divisia method I (LMDI I). A related version, the LMDI II, has a weighting scheme slightly more complex than LMDI I (Ang *et al.*, 2003).
Source: Ang (2004).

As regards studies conducted on emissions, the overall trend has been that the industrial sector of advanced economies has seen a substantial drop in carbon intensity owing to improvements in energy intensity and the transition to cleaner fuel. Further, China has achieved a considerable decline in CO_2 emissions mainly due to the improved energy intensity (Zhang *et al.*, 2009; Ma *et al.*, 2018). Liaskas *et al*. (2000) have found that industrial CO_2 emissions in 13 European Union countries have decreased during 1973-93. The stimulus for the reduction in the sub-period 1973-83 came from the oil crisis of 1973 which led to the reduction in energy intensity across all industries. In the second sub-period of 1983-93, the reduction primarily emanated from switching to cleaner fuels, reflecting growing environmental concerns.

In India's case, Sahu and Narayan (2010) used the generalised parametric divisia index (GPDI) to segregate the energy intensity effect and found that the energy intensity in India's manufacturing sector has fallen during the period 1990-2000 due to the changing share of various industries in total industrial output. In another paper, Sahu and Narayan (2014) analysed the trends in CO_2 emissions in India's manufacturing sector, specifically at the firm level, from 2000 to 2011. They found that emission intensity differed as per various identifiable firm-level characteristics, such as age, size, capital intensity, labour intensity and technology. A brief overview of carbon decomposition studies done in various countries is enumerated in Table 2.

Table 2: Overview of Cross-Country Carbon Decomposition Studies

Paper	Country	Method Used	Major Findings
Akbostanci *et al.* (2011)	Turkish manufacturing sector (1995-2001)	LMDI	Changes in total industrial activity and energy intensity were the main factors for CO_2 changes.
Kim and Jeong (2013)	South Korea manufacturing sector (1991-2009)	LMDI	Structural effects and energy intensity effects play a major role in reducing energy consumption and greenhouse gas emissions, and the structural effect is greater than the energy intensity effect.
Hammond *et al.* (2012)	UK manufacturing industry (1990-2007)	LMDI	The decline in energy intensity was the main factor in the reduction of carbon emissions.
Lee and Kim (2021)	South Korea manufacturing sector (2006-2018)	LMDI	Output effect increased the CO_2 emissions, which was mitigated by the energy intensity effect and structural effect.
Zhang *et al*. (2015), Ma *et al. (2018*)	China's manufacturing sector (2004-2014)	LMDI	Output effect had a positive effect on CO_2 emissions, which was offset by the energy intensity effect.
Sahu and Narayan, 2010	India's Manufacturing sector (1990-2000)	GPDI	Energy intensity in India's manufacturing sector has fallen because of changing share of various industries in total industrial output.
Paul *et al.* (2004)	India's primary, secondary and service sectors (1980-1996)	Sun	Energy intensity reduces CO_2 emissions in the industrial and transport sectors.
Das and Roy (2020)	India's Primary, Secondary and service sectors (1990-2013)	LMDI	Energy intensity effect was the main factor which offsets the output effect.
Dasgupta *et al*. (2017)	Indian manufacturing sector (1973-2012)	LMDI	Energy efficiency has contributed to the decoupling of emissions from industrial activity growth. A major driver of growth in energy demand is due to the output effect with marginal impact from structural change.
G. Ortega-Ruiz *et al.,* (2018)	India's primary, secondary and service sectors (1990-2015)	LMDI	The economic growth of India has been the dominating driving force contributing to the increase in CO_2 emissions, while the improvement in energy intensity has been the major factor in reducing the emissions.

Section III
Methodology

III.1 LMDI Decomposition

Based on the energy identities, CO_2 emissions from industry can be decomposed into five factors: output effect, structural effect, energy intensity effect, fuel mix effect and emission factor effect (Table 3).

The decomposition identity is expressed as:

$$C = \sum_{ij} C_{ij} = \sum_{ij} Q \frac{Q_i}{Q} \frac{E_i}{Q_i} \frac{E_{ij}}{E_i} \frac{C_{ij}}{E_{ij}} = \sum_{ij} Q S_i I_i M_{ij} U_{ij} \qquad ...(1)$$

Where C is the total CO_2 emissions and C_{ij} is the CO_2 emissions arising from the consumption of fuel *j* by industrial sector *i*; $Q(=\sum_i Q_i)$ is the output effect; $S_i(=\frac{Q_i}{Q})$ is the structural effect; $I_i(=\frac{E_i}{Q_i})$ is the energy intensity effect; E_{ij} is the energy consumption from fuel *j* in industrial sector *i*, where $E_i = \sum_j E_{ij}$ is the total energy consumed by industry *i* from all fuels; the fuel-mix variable is given by $M_{ij}(=\frac{E_{ij}}{E_j})$ and the CO_2 emission factor by $U_{ij}(=\frac{C_{ij}}{E_{ij}})$.

$$\Delta C_{tot} = C_T - C_0 = \Delta C_{out} + \Delta C_{str} + \Delta C_{int} + \Delta C_{mix} + \Delta C_{emf} \qquad ...(2)$$

The subscripts denote output effect (out), structural effect (str), energy intensity effect (int), fuel mix effect (mix) and emission factor effect (emf). The LMDI formulae for these effects are expressed as below:

$$\Delta C_{out} = \sum_{ij} \frac{C_{ij}^T - C_{ij}^o}{lnC_{ij}^T - lnC_{ij}^o} \ln\left(\frac{Q^T}{Q^O}\right) \qquad ...(2.1)$$

$$\Delta C_{str} = \sum_{ij} \frac{C_{ij}^T - C_{ij}^o}{lnC_{ij}^T - lnC_{ij}^o} \ln\left(\frac{S_i^T}{S_i^O}\right) \qquad ...(2.2)$$

$$\Delta C_{int} = \sum_{ij} \frac{C_{ij}^T - C_{ij}^o}{lnC_{ij}^T - lnC_{ij}^o} \ln\left(\frac{I_i^T}{I_i^O}\right) \qquad ...(2.3)$$

$$\Delta C_{mix} = \sum_{ij} \frac{C_{ij}^T - C_{ij}^o}{lnC_{ij}^T - lnC_{ij}^o} \ln\left(\frac{M_{ij}^T}{M_{ij}^O}\right) \qquad ...(2.4)$$

$$\Delta C_{emf} = \sum_{ij} \frac{C_{ij}^T - C_{ij}^o}{lnC_{ij}^T - lnC_{ij}^o} \ln\left(\frac{U_{ij}^T}{U_{ij}^O}\right) \qquad ...(2.5)$$

Table 3: Decomposition of CO_2 Emissions

Decomposed Component	Description
Output effect	Change in emissions explained by the change in output
Structural effect	Change in emissions explained by the change in the structure of overall industry *i.e.*, change in individual share of contribution to industrial GDP
Emission intensity effect	Change in emissions due to change in energy intensity of individual sectors defined as the energy consumed per unit GVA output. This signifies efficiency in production techniques or the use of better capital equipments
Fuel-mix effect	Change in emissions due to shifts to different fuel

In our calculations, we assume no change in emission factors of fuels, *i.e.*, $U_{ij}^{0} = U_{ij}^{T}$, and therefore, the ΔC_{emf} becomes zero.[2] Also, since LMDI uses logarithmic functions, it cannot handle zero values but this problem can be overcome by using small positive numbers (*e.g.*, 10^{-20}). Ang and Choi (1997) have shown that the LMDI tends to converge when the zero values in the data set are replaced by a small positive number. The other limitation of LMDI is its inability to process negative values. However, in our dataset, only a few sectors have negative GVA and a negligible share in the overall output. Such sectors have been dropped from the analysis without contaminating the results.

III.2 Data

The Annual Survey of Industries (ASI) publishes fuel consumption data at the aggregate and firm levels. Being handy to use, aggregate data has found several applications in various national-level analyses. However, firm-level raw data have remained relatively unexplored by researchers on estimations of CO_2 emissions. This paper distinguishes itself from previous studies in its use of granular firm-level data and the application of multipliers to arrive at the aggregate statistics. While the aggregate data combines many different fuel categories, thereby rendering it impossible to track the consumption of

[2] The most authoritative data on emission factors is released by Intergovernmental Panel on Climate Change (IPCC), however, emission factors are not measured frequently. This is because fuel quality is strictly regulated by the authorities and the refining processes guarantee uniform quality standard. The last guidelines on emission factors of fuels were given by IPCC in 2006. Therefore, our assumption of emission factors being constant is not unrealistic.

individual fuels, the granular data retains the fuel consumption segregation to a greater extent, and therefore, has been preferred for this analysis.

The ASI survey is comprehensive with around 57,000, 58,000 and 67,000 establishments surveyed in 2009-10, 2013-14 and 2017-18, respectively, out of over 2 lakh firms in the ASI frame, which is a list of all factories/units registered with the government authorities and updated periodically by the National Statistical Office (NSO) in consultation with the Chief Inspector of Factories in states. We choose these panel years as they follow the same industrial classification code (National Industrial Classification (NIC)-2008) and yet have a sufficient gap between them to capture structural changes in CO_2 emissions from manufacturing industries.

The ASI provides a firm-level break-up of fuel inputs namely, electricity; coal; and gas in physical units. For petroleum products, expenditure incurred on petrol, diesel, furnace oil, lubricants and others is provided instead of quantities. Expenditure on other fuels, such as firewood, fuel oil, solar energy and others, is also provided. The physical quantities of petrol, diesel, furnace oil, lubricants, and other consumed fuels are unavailable. However, the combined expenditure incurred on these fuels has been provided. In order to estimate the quantity of individual fuels consumed from the consolidated fuel expenditure on petroleum products, we need to have two things – first, the historical prices of fuel in India for 2009-10 and 2017-18; and second, the proportion of expenditure incurred on each fuel type. As historical prices of individual fuel categories are not available, we back-calculated the prices using their current dealer prices on "Fuels India" website with the wholesale price index (WPI) published by the Office of Economic Advisor, Department for Promotion of Industry and Internal Trade (DPIIT), Government of India.[3]

$$Fuel\ Price_{hist} = \frac{WPI_{hist}}{WPI_{current}} \times Fuel\ Price_{current} \qquad ...(3)$$

Where the subscript *hist* stands for panel years 2017-18, 2013-14 and 2009-10.

In the absence of the proportion of expenditure incurred on each fuel type, a simplifying assumption has been made that all sectors in the industry

[3] https://eaindustry.nic.in/download_data_1112.asp

Table 4: Consumption Pattern and Share of Petroleum at the Industrial Level

(Consumption in '000 tonnes)

Petroleum Fuel	Industrial Consumption (2017-18)	Share in Industry	Industrial Consumption (2013-14)	Share in Industry	Industrial Consumption (2009-10)	Share in Industry (2009-10)
High Speed Diesel	1304	0.34	751	0.27	1645	0.27
Furnace Oil	2400	0.63	1909	0.69	4360	0.72
Kerosene	97	0.03	107	0.04	69	0.01

Sources: Energy Statistics of India; and Authors' calculations.

use different forms of petroleum fuels in roughly the same proportion. We have assumed a constant proportion of petroleum products across all industries as obtained from industrial consumption of petroleum products (Table 4).

For petroleum products, a wide array of fuels is available, for example, LPG, Natural Gas, Petrol, Kerosene, Aviation Turbine Fuel (ATF), High-Speed Diesel (HSD), Light Diesel Oil (LDO), Furnace Oil, low sulphur heavy stock (LSHS), Lubricants, Naphtha and others. Out of these, fuels commonly used in industry are – HSD, LDO, LSHS, and FO. Although widely used in the transportation sector, petrol does not find wide usage in industries as fuel.[4] We have merged LDO with HSD, and LSHS with Furnace Oil to keep the calculations simple without affecting the results much. Further, their WPI indices are not available separately, and the difference in their emission factors is also not significant.

We back-calculated the physical quantities of consumption of these fuels using average historical prices for the constituent fuel types. As fuel prices may vary for companies depending on wholesale contracts, regional taxes and other factors, an indicative price has been taken to keep the analysis simple. Using the price of various petroleum products prevailing at that time, the physical quantities of the fuels consumed have been estimated. The calorific value of the fuels is then used to calculate the energy content of the fuels (Table 5). The conversion into energy units brings all fuel types into the same unit (kWh), making them comparable across the board, which are

[4] According to a study conducted by M/s Nielsen (India) Pvt Ltd for Petroleum Planning and Analysis Cell (PPAC) of Petroleum Ministry in 2014, 99.6 per cent of petrol is used in the transport sector.

Table 5: Calorific Value and Emission Factor of Various Fuels

Fuel	Calorific Value (kWh/MT)	Emission Factor (kg CO_2 per kWh)
Diesel	12,552	0.2496
Furnace Oil	12,203	0.2496
Kerosene	12,901	0.2566
Coal	4,350	0.3230
LPG	13,830	0.2106
Fuel Oil	11,950	0.2491
Electricity	-	0.82
Solar energy	-	0

Note: Emission factor of electricity has been documented to be constant in the period 2013-18 as given in CO_2 Baseline Database for the Indian Power Sector User Guide December 2018 issued by Central Electricity Authority (CEA), Ministry of Power, Government of India, pp 27.
Sources: Bureau of Energy Efficiency (BEE); Environmental Protection Agency (EPA); and CEA.

otherwise expressed in different weight/volume/energy units. The emission factor of the fuels (CO_2 emissions per unit of energy) is then multiplied with the energy units produced from the combustion of fuels.

$$CO2_{fuel} = Energy_{fuel} \times Emission\ factor \qquad ...(4)$$

It may be noted that electricity is a secondary source of energy which is generated using primary sources like coal, petroleum products, gas, and renewables and therefore, is not a clean form of energy in the true sense unless all the electricity produced in the country comes from a renewable source. We do not treat electricity as a clean source of energy. It has an emission factor of 0.82 which accounts for indirect emissions caused due to the combustion of coal and heat losses during its generation, and losses in the distribution network. Furthermore, the indirect energy consumed during electricity generation from primary energy sources like coal, gas, *etc*. does not form a part of energy intensity calculations.

Section IV
Stylised Facts

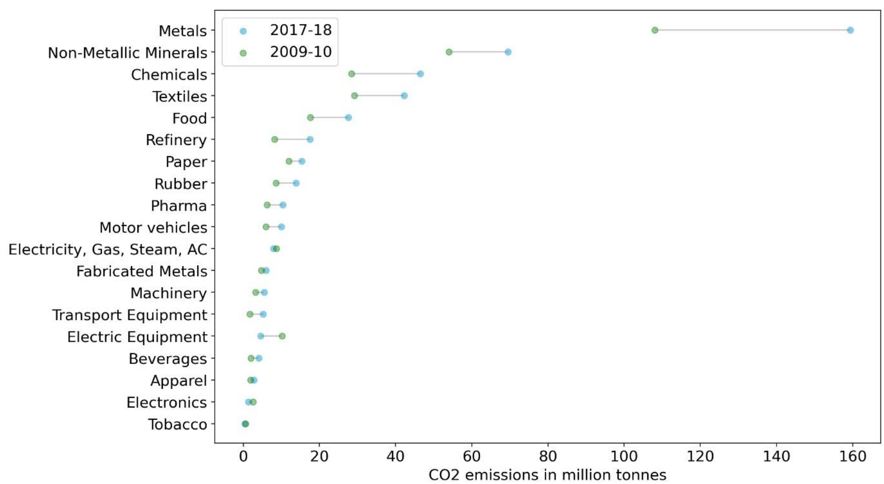
IV.1 Total Emissions across Sectors

Basic metals, non-metallic minerals, chemicals, textiles, food industries and refineries are the largest contributors to CO_2 emissions comprising around 80 per cent of the emissions from the manufacturing sector (Chart 1). These sectors play a vital role in creating employment and provide crucial support to the economic development of the country, but they also have high CO_2 emissions per unit GVA. Amongst the key sectors, the manufacture of electrical equipment has undergone a reduction in aggregate emissions due to the reduction in energy consumption on account of greater energy-efficient production processes. It is noteworthy that the growing share of electricity in the energy consumption basket is also responsible for increasing CO_2 emissions. It is because even though the direct emission from electricity is zero, the use of fossil fuels in power generation emits around 2.5 times more CO_2 than the direct combustion of coal after accounting for the loss of heat during power generation and loss of electricity during transmission.

IV.2 Energy Consumption and Carbon Intensity

The energy consumption by industries has increased by 21.5 per cent accompanied by an increase of 39.9 per cent in CO_2 emissions over the base period. These sectors have contributed to an increase of 78 per cent in GVA (Table 6). Carbon intensity, measured in terms of CO_2 emitted per unit rupee

Chart 1: Change in CO_2 Emissions by Different Sectors



Note: Only industries contributing more than one per cent share in GVA for both panel years have been depicted in the chart for the sake of clarity.
Source: Authors' calculations based on ASI data.

Table 6: Aggregate Data for Manufacturing Firms in ASI Data

Year	Energy (billion kWh)	CO_2 (million tonnes)	GVA (2011-12 ₹ trillion)	Energy Intensity (kWh per ₹ GVA)	Carbon Intensity (g per ₹ GVA)
2009-10	947.2	327.9	7.13	0.133	46.0
2013-14	1078.3	419.2	9.46	0.114	44.3
2017-18	1151.4	458.9	12.69	0.091	36.2

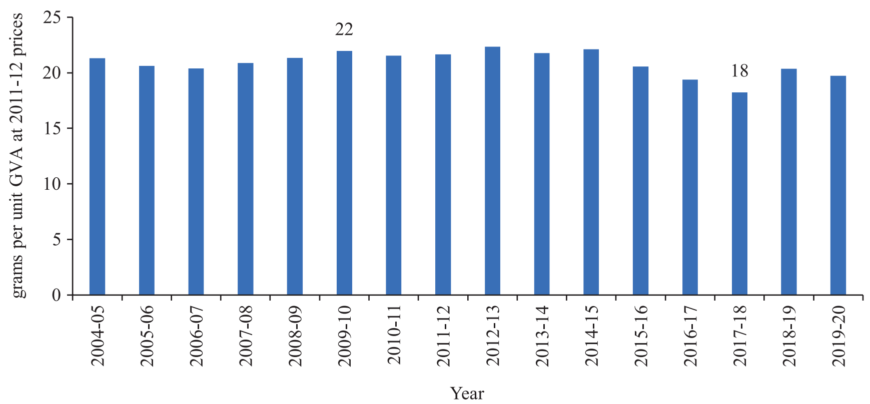
Source: Authors' calculations based on ASI data.

GVA by the manufacturing sector, has decreased from 46g to 36g per rupee GVA which reflects a swifter green transition as compared to the overall economy for which the carbon intensity has only seen a decline from 22g to 18g per rupee GVA (Chart 2).

IV.3 Energy and Carbon Footprint of Micro, Small and Medium Enterprises (MSME) Industries

In our analysis, we have used investment in plant and machinery and turnover to classify firms into micro, small and medium enterprises with residual firms being classified under the large category.[5] For a uniform

Chart 2: CO_2 Emissions per GVA: Overall Economy



Sources: World Bank; and Authors' calculations.

[5] A revision in MSME definition came into effect from 1st July 2020. As per revision, the definition of micro manufacturing and services units was increased to ₹ 1 Crore of investment and ₹ 5 Crore of turnover. The limit of small unit was increased to ₹ 10 Crore of investment and ₹ 50 Crore of turnover. Similarly, the limit of medium unit was increased to ₹ 20 Crore of investment and ₹ 100 Crore of turnover.

Table 7: Energy and Carbon Intensity of MSME and Large Industries

	Energy Intensity (kWh per ₹ GVA)			Carbon Intensity (g per ₹ GVA)		
	2009-10	**2013-14**	**2017-18**	**2009-10**	**2013-14**	**2017-18**
Micro	0.12	0.11	0.09	50.7	48.4	39.2
Small	0.10	0.09	0.08	43.1	40.2	34.3
Medium	0.08	0.08	0.06	35.8	36.7	30.1
Large	0.14	0.13	0.10	44.1	47.0	38.1

Source: Authors' calculations based on ASI data.

comparison across time horizon, we take the deflated values of thresholds for classification. We find that an increase in the size of MSME industries is associated with lesser energy and carbon intensities. However, large industries have high energy and carbon intensity almost at par with micro industries (Table 7). A salient decline in intensities is also observed across various sizes for different years. It indicates that firms can deploy more capital equipment with size and reap the benefits of scale. On the other hand, despite having economies of scale in production, large industries are inherently energy and carbon-intensive because of the distinct nature of output produced. This is corroborated by Sahu and Naraynan (2011), who found a non-linear (U-shaped) relationship between energy intensity and firm size, implying that both very large and very small firms tend to be more energy intensive as compared to the medium size firms.

IV.4 Fuel Mix of MSMEs

Coal is the primary energy source for large firms making them less dependent on purchased electricity. Many large firms meet their electricity requirements through *in situ* production of electricity. The MSME sector, in comparison, uses much more purchased electricity in its fuel mix (Table 8). Electricity is increasingly gaining a greater share in the energy mix of industries. Also, a rise in the energy share of coal during the first sub-period is conspicuous; however, it declined during the latter sub-period.

Table 8: Fuel Mix of MSMEs

(in per cent)

	Period	Coal	Diesel	Gas	Furnace oil	Kerosene	Electricity	Others
Micro	2017-18	32.9	6.9	3.6	12.3	0.5	30.6	13.2
Micro	2013-14	40.8	3.4	3.2	8.5	0.5	29.2	14.3
Micro	2009-10	38.3	4.8	4.4	12.4	0.2	25.9	14.0
Small	2017-18	29.9	7.8	6.7	14.0	0.6	32.8	8.3
Small	2013-14	32.8	4.3	7.4	10.8	0.7	34.6	9.4
Small	2009-10	26.8	6.0	7.4	15.5	0.3	32.0	12.1
Medium	2017-18	24.1	6.8	7.1	12.1	0.5	39.1	10.2
Medium	2013-14	30.6	4.2	5.2	10.4	0.6	38.3	10.6
Medium	2009-10	25.0	6.2	3.8	15.9	0.3	34.2	14.6
Large	2017-18	50.6	4.4	9.7	7.8	0.3	18.6	8.6
Large	2013-14	52.0	2.1	10.5	5.1	0.3	16.8	13.2
Large	2009-10	46.0	3.1	21.0	8.1	0.1	11.0	10.7

Source: Authors' calculations based on ASI data.

Section V
Empirical Analysis

V.1 Decomposition of Energy

The results of the LMDI decomposition need to be interpreted as *ceteris paribus* effects. The LMDI decomposition of energy consumed by the manufacturing sector shows that the activity (output) effect would have led to a rise of 597 billion kWh in energy consumption, if all other things were constant. In the absence of structural and energy intensity effects, an increase in the output alone would have required an increase in energy consumption almost three times the actual change in energy consumption. Nevertheless, the energy demand was subdued mainly because of the negative energy intensity effect and the structural effect. We reproduce results obtained from the Shapley-Sun method for the robustness check (Table 9). While output and energy intensity effects are consistent with both methods, the effect of structural change on energy consumption seems less conclusive. Nevertheless, its magnitude is minuscule as compared to absolute base year emissions.

Table 9: Results of Additive Decomposition of Energy (billion kWh)
(Period 2009-10 to 2017-18)

Method	Base year emissions	Output effect	Structural effect	Energy intensity effect
LMDI	921	597	-69	-322
Shapley/Sun	921	640	23	-457

Source: Authors' calculations based on ASI data.

V.2 Decomposition of CO_2 Emissions

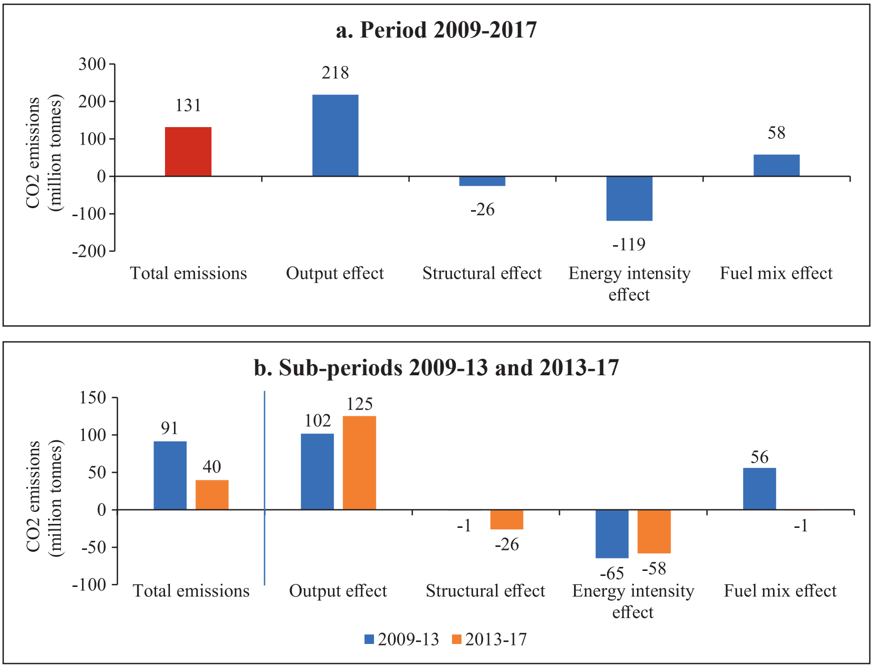
For the decomposition of CO_2 emissions, the LMDI may be extended to include two more variables, namely, the fuel mix effect and the emission factor effect. Since we assume no change in fuels' emission factor in this period, we have decomposed CO_2 emissions into output, energy intensity, structural and fuel mix effects. CO_2 emissions from registered manufacturing industries have risen by 131 million tonnes (MT) during 2009-10 to 2017-18. The LMDI decomposition shows that total change in CO_2 emission can be decomposed into a positive activity effect (+218 mt) and fuel mix effect (+58 mt), which is partially neutralised by a negative energy intensity effect (−119 mt) and the structural effect (−26 mt).

The increased output activity is the most significant contributor to emissions. However, the actual increase in emissions is lower because of a reduction in sectoral energy intensity and structural changes in the manufacturing sector. Changes in fuel mix have also contributed positively to CO_2 emissions implying greater use of carbon-intensive fuels over the years (Chart 3a). We break down the eight-year period into two equal sub-periods 2009-13 and 2013-17 to investigate the individual effects. We observe that while output and structural effects remain prominent, there is a radical shift in structural and fuel mix effects, and the reasons for these are explained in later sections (Chart 3b).

V.3 Output Effect

Our results are in conformity with those from an overwhelming majority of other studies which show a significant contribution of activity growth in driving the increased energy use and CO_2 emissions. A related concept is the decoupling of energy related emissions from economic output growth. The

Chart 3: Additive Decomposition of CO_2 Emissions



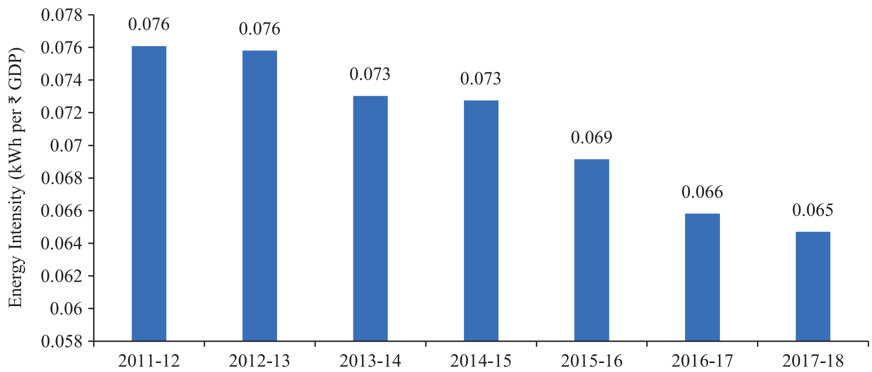
Source: Authors' calculations based on ASI data.

magnitude of decoupling elasticity measured as $\frac{\Delta C/C}{\Delta GDP/GDP}$ is used to assess the techno-economic performance. Das and Roy (2020) estimated the decoupling elasticity for the industrial sector to be 0.38 for the 2006-13 period. We found the value of decoupling elasticity to be 0.51 during the 2009-10 to 2017-18 period [($\Delta C/C = 0.40$) and ($\Delta GDP/GDP = 0.78$)]. Any value that lies between 0 and 0.8 is considered to be decoupled, which means per cent change in emissions is less than the per cent change in output (Tapio, 2005).

V.4 Energy Intensity Effect

Output growth is the primary driver of CO_2 emissions, while improvement in energy intensity profoundly reduces CO_2 emissions (Dasgupta and Roy, 2001; Dasgupta and Roy, 2017). The energy intensity effect alone, *ceteris paribus*, would have reduced 122 million tonnes of CO_2. In other words, the total emission increase was 131 million tonnes during this period. Energy intensity (Energy consumption per unit GVA) has improved from 0.133 to 0.091 kWh/₹ (at 2011-12 prices). This amounts to a reduction

Chart 4: Energy Intensity of India



Note: GDP for various years is reported at 2011-12 prices.
Source: Energy Statistics of India.

of almost 31.5 per cent over the base year. In contrast, the energy intensity of India's GDP declined by 14.5 per cent only from 0.076 kWh/₹ to 0.065 kWh/₹ at 2011-12 prices during 2009-10 to 2017-18 (Chart 4). A swifter transformation to energy-efficient processes is underway in the manufacturing sector as compared to the economy as a whole.

A large share of energy efficiency can be attributed to the continuous techno-economic improvements and firms catching up to the international best practice benchmarks. Another trend which is driving energy efficiency is the growing share of electricity. Electricity is a secondary energy source (produced from primary sources like coal, diesel, gas, renewables, *etc*.) which is highly efficient at the point of consumption *vis-à-vis* the *in situ* generation of heat and electricity from conventional fuels like coal, diesel and gas. The transformation losses, (*i.e.,* losses when heat energy is converted into electrical energy) and transmission and distribution losses in electricity generation are even more significant than the *in situ* generation of heat and electricity. When we consider delivered energy at the point of consumption, electricity is the most efficient among all the fuels. However, the effect of electrification on CO_2 emissions is not straightforward and is discussed later in the fuel mix section.

The most energy-intensive industries are basic metals, non-metallic mineral industries, paper, chemical industries, and textiles. These industries

Table 10: Energy Intensities of Top Five CO_2 Emissions Industries (2017-18)

Activity	2009-10	2017-18	Percentage reduction
Manufacture of basic metals	0.38	0.31	18.4
Manufacture of other non-metallic mineral products	0.33	0.30	9.1
Manufacture of chemicals and chemical products	0.13	0.11	15.4
Manufacture of textiles	0.18	0.14	22.2
Manufacture of food products	0.09	0.07	22.2

Note: Energy intensity units are kWh per rupee GVA.
Source: Authors' calculations based on ASI data.

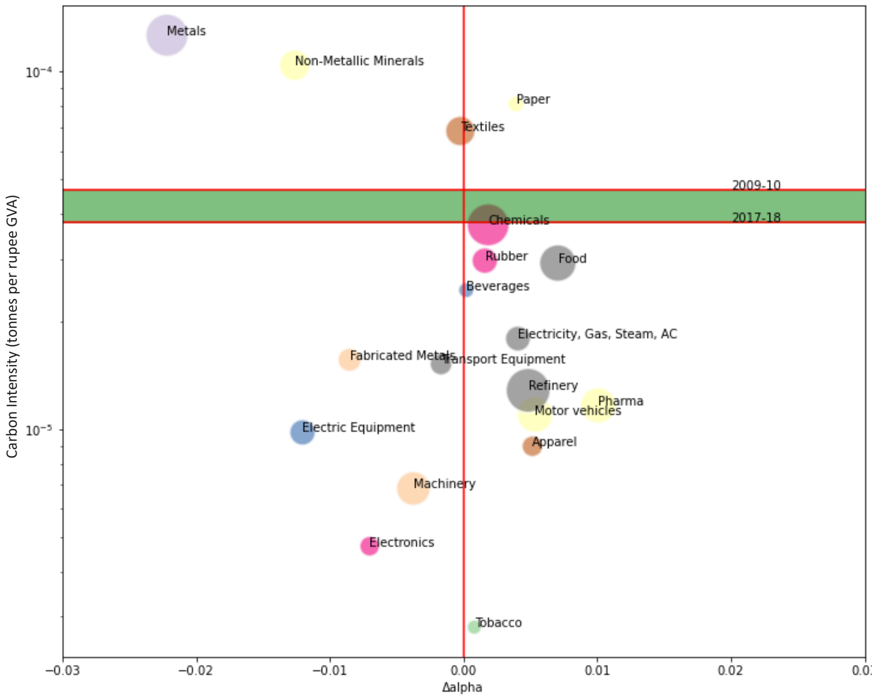
used 73.5 per cent of energy while their contribution to GVA was only 31.3 per cent in 2017-18. A broad decline in energy intensity was observed across all sectors, as mirrored in the top five carbon-emitting sectors (Table 10).

V.5 Structural Effect

Structural changes are not discernible over short horizons. Therefore, a long horizon of eight years (2009-10 to 2017-18) has been considered to visualise its effect. It essentially refers to the increase in the share of industries (Δalpha) with less carbon footprint, accompanied by a decrease in the share of high carbon-intensive industries in the aggregate output. The bi-pronged nature of structural shift can be visualised from the second and fourth quadrants of the scatter plot with Δalpha and carbon intensity depicted on the x and y-axis, respectively (Chart 5).

Many industries with low carbon footprints such as manufacturing food products, motor vehicles, trailers and semi-trailers, pharmaceutical, apparel, medicinal and botanical products have gained a larger share in GVA output. On the other side, high carbon-intensive industries like basic metals and non-metallic minerals have witnessed a declining share in GVA. The mild structural effect indicates that the economy is slowly moving towards cleaner industries. However, it is unable to neutralise the increase due to the output effect. Upon breaking down into two equal sub-periods, the structural effect in the latter (2013-17) is conspicuously more prominent than the former (2009-13) as shown in Annex A1 with many sectors being concentrated in the fourth quadrant.

Chart 5: Structural Shift in Industry



Note: The vertical and horizontal red lines forming the quadrants correspond to zero change in share of GVA between 2009-10 and 2017-18 and average carbon intensity, respectively. Quadrant 1: High carbon industries gaining greater share in GVA; Quadrant 2: High carbon industries with a declining share in GVA; Quadrant 3: Low carbon industries with a declining share in GVA; Quadrant 4: Low carbon industries gaining greater share in GVA.
Source: Authors' calculations based on ASI data.

V.6 Fuel Mix Effect

A more significant share of cleaner fuels in the overall energy consumption basket causes a decline in CO_2 emissions (Zhang *et al*., 2015; Muangthai *et al.,* 2014). For Indian manufacturing, the share of coal and electricity in the overall energy mix has increased during the study period resulting in a positive contribution to emissions (Table 11). Notably, the usage of gas-based fuels in industry, which are cleaner fuels than coal, has come down mainly due to a fall in domestic production of natural gas (Safari *et al*., 2019). As India's estimated reserves of natural gas resources are limited (less than 1 per cent of the global natural gas reserves), improving import logistics and infrastructure can help to increase the share of gas in domestic

Table 11: Share of Fuels in the Indian Manufacturing Sector

Fuel (as per cent of energy mix)	2009-10	2013-14	2017-18
Coal	40.8	47.2	45.0
Gas (LPG, Biogas, Natural Gas, Coal Gas)	17.9	9.3	8.9
Diesel	3.8	2.6	5.1
Furnace Oil	9.8	6.4	9.1
Kerosene	0.2	0.4	0.4
Electricity	16.3	21.5	23.0
Other (Wood, Solar, Fuel Oil)	11.3	12.6	8.5

Source: Authors' calculations based on ASI data.

fuel consumption. A breakup of decomposition analysis for the periods 2009-13 and 2013-17 reveals that the fuel mix effect has drastically reduced in the latter period indicating a cleaner fuel mix. The large fuel mix effect in the period 2009-13 is on account of an increase in the share of coal and electricity, however, the negligible fuel mix effect in the latter period is due to the balancing effect of the increasing share of electricity and decreasing share of coal.

The curious case of electricity merits further attention. Electrification in transport and industry is hailed as the next big revolution combating climate change. Electricity is a very efficient source of delivered energy compared to other fossil fuels. However, countries that overwhelmingly use coal or lignite to fire their power stations eventually emit much higher CO_2 per kWh of energy. In India, one kWh of grid electricity used at the point of consumption emits 0.82 kg of CO_2 that is three to six times more polluting than other sources. In a traditional coal-fired power plant, the transformation loss (chemical energy of coal to heat energy to electrical energy) is around 70-73 per cent. Furthermore, 21 per cent of the remaining electricity is lost in transmission and distribution. The higher efficiency somewhat compensates for the higher emission factor, but on the net, grid electricity remains highly carbon-intensive in India.

Section VI
Conclusions

Using firm-level data on fuel consumption and expenditure from ASI survey, this paper finds that basic metals, non-metallic minerals, textiles, chemicals, food and refineries are the biggest contributors to CO_2 emissions, together accounting for 80 per cent of the CO_2 emissions from the formal manufacturing sector. India's manufacturing sector, however, is undergoing a faster process of green transformation than the overall economy. The carbon intensity of the manufacturing sector has declined from 46g to 36g per rupee of GVA during the period 2009-10 to 2017-18 while that of the overall economy has reduced from 22g to 18g per rupee of GVA.

Our decomposition analysis of CO_2 emissions in the manufacturing sector in India shows that the manufacturing output and fuel mix effects have contributed to the increase in total CO_2 emissions. In contrast, the energy intensity and structural effects have helped in abating total CO_2 emissions. On a net basis, the effect of all four factors amounts to an increase of 131 million tonnes of CO_2 emissions during 2009-10 to 2017-18. The findings of this paper are in line with other studies which show a significant role of output growth in driving the increased energy use and resultant CO_2 emissions.

Though the structural effect has led to a reduction in the CO_2 emissions from the manufacturing sector, it has remained low. The shift towards greener industries can be further incentivised through appropriate fiscal measures involving taxes and subsidies. Energy intensity, on the other hand, is the largest factor which has led to a reduction in CO_2 from the manufacturing sector as most manufacturing units use electricity as an input for production. While electricity generated from coal may be the most significant source of CO_2 emissions, it could negate some of the benefits of reduced energy intensity through the fuel mix effect reported in this paper. Energy intensity can be further reduced through greater innovation in the field of green technology. It has been observed that innovation in greener technologies is mainly concentrated in developed countries. Increasing public spending on research and development, overseeing effective intellectual property rights regimes and fostering international collaboration can encourage innovation in greener technologies and help in further reduction of CO_2 emissions in the long-term.

Increasing the share of renewable energy (for example, hydro, solar, and wind) in electricity generation can be a game-changer. The effort to augment renewable energy use by notifying the rules for Promoting Renewable Energy through Green Energy Open Access by the Central Government is a step in the right direction towards adopting green energy alternatives. These rules will help in the transition to private renewable energy procurement.

References

Akbostanci, E., Tunç, G. Ipek, & Turut-Asık, S. (2011). CO_2 emissions of Turkish manufacturing industry: A decomposition analysis. *Applied Energy,* 88(6), 2273-2278.

Ang, B. W. (2004). Decomposition analysis for policymaking in energy. *Energy Policy*, *32*(9), 1131–1139.

Ang, B. W. (2005). The LMDI approach to decomposition analysis: A practical guide. *Energy Policy*, *33*(7), 867–871.

Ang, B.W. & Choi, K.H. (1997). Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. *The Energy Journal, 18* (3), 59– 73.

Ang B.W. & Liu F.L. (2001). A new energy decomposition method: Perfect in decomposition and consistent in aggregation. *Energy*, *26* (6), 537-548.

Ang B.W., Liu F.L. & Chew E.P. (2003). Perfect decomposition techniques in energy and environmental analysis. *Energy Policy*, *31*(14), 1561-1566.

Balk, B.M. (1996). Consistency-in-aggregation and Stuvel indices. *Review of Income and Wealth, 42* (3), 353– 363.

Biswas, T., Ganesan, K., & Ghosh, A. (2019). Sustainable Manufacturing for India's Low-carbon Transition: Four bets for Hard-to-abate Sectors. Issue Brief. New Delhi: *Council on Energy, Environment and Water.*

Chung, H.S. & Rhee, H.C. (2001). Carbon Dioxide Emissions of Korea and Japan and Its Transmission via *International Trade. International Economic Journal, Taylor & Francis Journals.* Vol. 15(4), 117-136.

Das, N. & Roy, J. (2020). India can increase its mitigation ambition: An analysis based on historical evidence of decoupling between emission and economic growth. *Energy for Sustainable Development*, *57*, 189-199.

Das Gupta, Meeth & Roy, Joyashree. (2001). Understanding Changes in Energy Consumption by Energy Intensive Manufacturing Industries in India. Staff Paper, CSO, Government of India.

Dasgupta, Shyamasree & Roy, Joyashree. (2017). Analysing Energy Intensity Trends and Decoupling of Growth from Energy Use in Indian Manufacturing Industries during 1973–1974 to 2011–2012. *Energy Efficiency.* Issue 4/2017.

G. Ortega-Ruiz, Mena-Nieto, A. & García-Ramos J.E. (2020). Is India on the right pathway to reduce CO_2 emissions? Decomposing an enlarged Kaya identity using the LMDI method for the period 1990–2016, *Science of the Total Environment*, Volume *737*.

Gupta, V., Biswas, T., & Ganesan, K. (2017). Greenhouse gases emission estimates from the manufacturing industries in India State level estimates: 2005 to 2013. *Council on Energy, Environment and Water (CEEW), India.*

Gupta, V., Biswas, T., Janakiraman, D., & Ganesan, K. (2019). Greenhouse gases emissions of India (subnational estimates): Manufacturing sector (2005-2015 series). *CEEW*.

Hammond, G. P. & Norman, J. B. (2012). Decomposition analysis of energy-related carbon emissions from UK manufacturing. *Energy, 41*, 220–227.

Jeong, K. & Kim, S. (2013). LMDI decomposition analysis of greenhouse gas emissions in the Korean manufacturing sector. *Energy Policy, 62*, 1245–1253.

Kim, S. (2017). LMDI decomposition analysis of energy consumption in the Korean manufacturing sector. Sustainability, 9(2), 202.

Lee, J. & Kim, J. (2021). A decomposition analysis of the Korean manufacturing sector: Monetary *vs.* physical outputs. *Sustainability*, *13*(11), 6192.

Liaskas, K., Mavrotas, G., Mandaraka, M. & Diakoulaki, D. (2000). Decomposition of industrial CO_2 emissions, *Energy Economics*, *22*(4), 383–394.

Ma, L., Chong, C., Zhang, X., Liu, P., Li, W., Li, Z. & Ni, W. (2018). LMDI decomposition of energy-related CO_2 emissions based on energy and CO_2 allocation Sankey diagrams: The method and an application to China. *Sustainability*, *10(*2), 344.

Muangthai, I., Lewis, C. & Lin, S.J. (2014). Decoupling effects and decomposition analysis of CO_2 Emissions from Thailand's thermal power sector. *Aerosol and Air Quality Research*, *14*, 1929-2938.

Park, S.H. (1992). Decomposition of industrial energy consumption. *Energy Economics*, *14*(4), 265–270.

Paul, S. & Bhattacharya, R. (2004). CO_2 emission from energy use in India: A decomposition analysis. *Energy Policy*, *32*, 585-593.

Qu, S. (2020). The decomposition analysis of carbon emissions: Theoretical basis, methods and their evaluations. *Chinese Journal of Urban and Environmental Studies*, *8*(4), 2050020.

Safari, A., Das, N., Langhelle, O., Roy, J. & Assadi, M. (2019). Natural gas: A transition fuel for sustainable energy system transformation? *Energy Science & Engineering*, *7*(4), 1075–1094.

Sahu, S.K. & Narayanan, K. (2010). Decomposition Of Industrial Energy Consumption In Indian Manufacturing: The Energy Intensity Approach. *Journal of Environmental Management and Tourism*, v. 1, n. 1, 22-38.

Sahu, S.K. & Narayanan, K. (2011). Determinants of energy intensity in Indian manufacturing industries: A firm level analysis. *Eurasian Journal of Business Economics, 4* (8), 13–30.

Sahu, S. K. & Narayanan, K. (2014). Energy Use Patterns And Firm Performance: Evidence From Indian Industries. *The Journal of Energy and Development*, *40*(1/2), 111–133.

Vartia, Y. (1976). Log-change index numbers. *Scandinavian Statistics,* 3, 121–126.

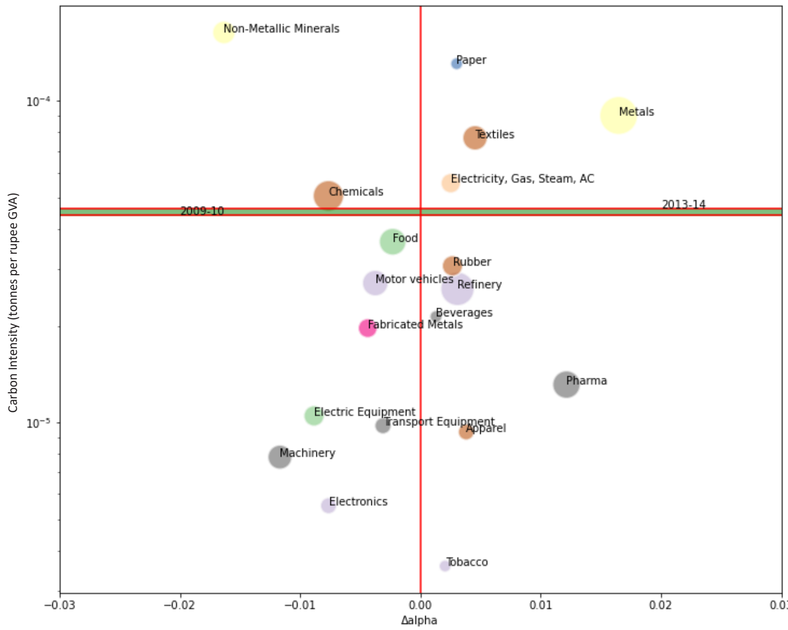
Wang, C. & Wang, F. (2015). Structural decomposition analysis of carbon emissions and policy recommendations for energy sustainability in Xinjiang. *Sustainability*, *7*(6), 7548–7567.

Zhang, M., Mu, H., Ning, Y., & Song, Y. (2009). Decomposition of energy-related CO2 emission over 1991–2006 in China. *Ecological Economics,* 68(7), 2122-2128.

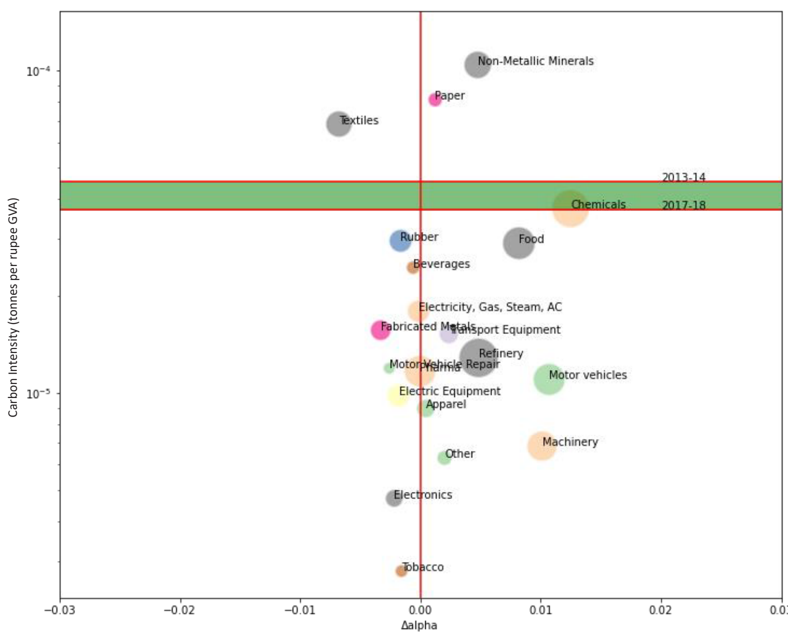
Zhang, X., Liu, Q., Liu, S. & Kong, L. (2015). Decomposition and decoupling analysis of energy - Related carbon emissions from China manufacturing. *Mathematical Problems in Engineering*, Hindawi Publishing Corporation.

Annex A1: Structural Effect during Sub-periods 2009-13 and 2013-17

a. 2009-13



b. 2013-17



Source: Authors' calculations based on ASI data.

Annex A2: Additive Decomposition of CO_2 (in percentages)

Activity	Energy Intensity Effect	Fuel Mix Effect	Output Effect	Structural Effect
Metals	-75	71	160	-56
Chemicals	-36	13	120	4
Non-Metallic Minerals	-75	11	262	-98
Textiles	-91	35	157	-1
Food	-77	24	131	23
Refinery	2	23	69	6
Rubber	-79	49	120	9
Pharma	-70	26	113	31
Motor vehicles	-76	47	113	15
Transport Equipment	80	-22	48	-5
Paper	-300	21	248	132
Machinery	-26	27	111	-11
Beverages	-8	22	84	2
Fabricated Metals	-135	79	275	-119
Motor Vehicle Repair	-346	-13	55	404
Other	-71	3	74	94
Apparel	-213	22	205	86
Waste Disposal	10	-3	23	68
Media	-60	22	133	6
Leather	-319	57	311	52
Furniture	-171	46	230	-5
Office Support	-64	-7	31	139
Publishing	-7	-33	262	-122
Personal Services	-970	25	179	866
Water Supply	-432	-28	75	485
Scientific activities	225	-13	-67	-45
Household Goods Repair	1831	-19	-134	-1579
Motion Picture	193	16	-51	-59
Wood	72	30	-850	848
Machine Repair	285	13	-73	-124
Tobacco	265	-9	-139	-17
Warehousing	1057	-166	-178	-614
Electricity, Gas, Steam, AC	1287	-501	-565	-121
Electronics	183	-43	-78	38
Electric Equipment	125	10	-67	33

Note: *Green and yellow shaded cells represent negative and positive contribution to emissions, respectively.

Source: Authors' calculations based on ASI data.

Reserve Bank of India Occasional Papers

Vol. 43, No. 1: 2022

Sensitivity of Pension Liabilities of Banks to Various Actuarial Assumptions

R. K. Sinha*

Received on: January 14, 2022
Accepted on: May 02, 2022

A reliable assessment of the future pension liabilities of any enterprise is critical to the overall enterprise risk management. For banks, in particular, information on the estimated quantum of variations in pension liabilities is useful for pro-active and prudent provisioning, which can have a long-term bearing on their balance sheets. The paper constructs salary indices for the Indian banking sector for the period 1987 to 2022 and provides a framework to decompose the rise in salary indices as a result of three components *viz.,* compensation for inflation, real increase that raises the purchasing power of salary, and rewarding merit. The indices are projected for the future and then used to compute benefits using the "Indian Assured Lives Mortality Table 2012-14 Ultimate" tables, enabling valuation (estimation) of various contingent liabilities of banks. The paper provides scenarios to assess the impact on employers' pension liabilities in future due to variations in key assumptions *viz.,* salary scales, decrement rates (mortality and attrition), and interest rate.

JEL Classification: J26, J31, J32, H55

Keywords: Actuarial present value, attrition rate, age retirement function, contribution function, decrement, salary scale, stress test

* R K Sinha (rajatsinha@rbi.org.in) is Director in the Monetary Policy Department (MPD), Reserve Bank of India. The author gratefully acknowledges the comments received from an anonymous reviewer, and also to Ranjeev, Assistant Adviser, Department of Statistics and Information Management (DSIM), who discussed the paper and offered his comments in the Department of Economic and Policy Research (DEPR) Study Circle Seminar. The author sincerely thanks officials of DSIM for their suggestions in earlier versions of the paper. The author is also thankful to Pallavi Chavan and her team in Development Research Group (DRG), DEPR for their valuable suggestions. The views expressed in the paper are those of the author and do not represent the views of the Reserve Bank of India.

Introduction

Salary is the cost of compensation paid by an employer for the services rendered by the employees. There are various forms of salaries *viz.,* fixed and variable, and the frequency of their disbursements may typically vary from daily (mostly applicable to daily wage workers) to monthly (in most of the cases) and sometimes on an *ad hoc* basis (especially for outsourced assignments or for contractual and consulting employees).

The size of escalation in the salary for a particular position[1] may change over time due to broadly two factors. One is inflation, which largely tracks benchmark inflation indices, such as the Consumer Price Index (CPI).[2] The other is the real increase in purchasing power, which reflects efforts directed at betterment of compensation to employees over time through various changes in the pay structure largely due to periodic wage revisions in the organisation. For an employee on the payroll, the salary could escalate due to a third factor *viz.,* merit, *i.e.,* an increase in the level of experience, knowledge, and maturity of the employees over the years after joining the organisation. The nominal growth of salary for an employee, thus, may differ from nominal growth in macroeconomic variables.

It is common for any organisation to provide some form of benefit to its employees, such as pension, gratuity, contributory provident fund (CPF), encashment of leave, *etc*. These benefits are typically long-term and are payable mostly at the time of retirement of the employee, as a lump-sum payment or through a series of regular payments. Therefore, these are also known as retirement benefits. These benefits can broadly be grouped into two categories, *viz.,* the defined benefit (DB) plan and the defined contribution (DC) plan under retirement benefit plans.

The defined benefit plan identifies the specific benefits that are payable at the time of retirement. They are mostly provided in the form of regular payments but start only after the employee retires. Pension is a common

---

1 The position is defined for a certain designation / grade with certain number of years of experience. The position of an employee changes every year with added number of years of experience and/or due to periodic promotion to the next grade.

2 The Consumer Price Index for the Industrial Workers (CPI-IW) is considered by most of the employers in India to compile the dearness allowance (DA), which is incorporated to reflect the inflationary rise in the salary.

example of this type. These regular payments are mostly linked to salary, which the employees draw just prior to their retirement. As the future salary is not known in advance, the DB plans may result in wide uncertainty with regard to the likely quantum of employers' liability for the future years.

Under the DC plan, the employer or the employee or both, make contributions on a regular basis, and the retirement benefit is according to the growth of the contributions. An example of this is the National Pension Scheme (NPS) in India, which is maintained and regulated by the Pension Fund Regulatory and Development Authority (PFRDA). The DC plan does not pose pension obligation risk (POR) to the employer. Many organisations (including banks) have switched over from DB plan to DC plan during the last two decades. Nevertheless, the employees with DB plans in the payroll of these organisations still pose significant POR till the retirement of all employees gets covered under the NPS.

The salary growth trend is important to take appropriate policy decisions, starting from wage settlement to assessment and valuation of future retirement liability and its impact on the balance sheet of an organisation. Indeed, it is an important aspect for a successful implementation of enterprise risk management (ERM) in any organisation.

The present paper attempts to construct salary indices for the Indian banking sector. It may be mentioned that the salary structure of many banks is either same or similar, especially those covered by the Indian Banks' Association (IBA). It may be noted that while the IBA provides a long series of pay scales for these banks, there has been limited research using these series to construct salary indices using these publicly available scales and publish the constructed indices in the public domain. This is potentially useful for any macroeconomic analysis, in addition to the internal use for the human resource (HR) - related assessment of the respective banks.[3]

The paper, thus, makes a useful contribution to the literature through an exhaustive study of not only the salary escalation in the banking sector but also of the sensitivity of actuarial assumptions on the actuarial present value (APV) of such liabilities. The paper is divided into six sections. The related literature

---

[3] At present, these banks have possibly outsourced the valuation of their contingent liability to some actuarial firms, which would have internally developed suitable salary indices for the necessary valuations.

pertaining to the present paper is reviewed in the second section of the paper. The third section provides definitions of select technical terms and describes the methodology of various computations apart from sources of data used. The computations of salary scales and various contribution and retirement functions are carried out in the fourth and fifth sections, respectively. The sixth section concludes the study and lays out the possibilities for further work on the subject.

Section II
Literature Review

The pension sector in India is still at a nascent stage but has gained importance in the recent times due to a large number of initiatives taken by the Government of India, Pension Fund Regulatory and Development Authority (PFRDA) and Institute of Actuaries of India (IAI). Nevertheless, the need for a reform in the pension fund in India was felt way back in the 1990s. Patel (1997) discussed the various challenges of pension reforms in India and suggested that international practices could be used with suitable changes for implementing these reforms.

The studies on salary indices are less common as against indices of other economic variables. This may be due to inherent complexity involving complex actuarial and statistical models and lack of expertise to carry out the work in the banks. As a result of this, construction of these indices is typically outsourced to actuarial firms to get the valuation of employer's pension liabilities. Further, even if such indices are computed, it is internally confined mostly to the HR sections of the banks. This has probably led to scarcity of studies based on such indices for public use.

There are a few organisations (*e.g.,* Kelly Services and Deloitte), which track salaries of enterprises and conduct surveys to estimate salary growth. The reports of these firms cover short-term increment in wages (say, over one year) and are useful in recruitment options. However, such studies and survey reports may not be suitable for an economy-wide use.

Among the few available studies, as part of research projects of Institute of Actuaries of India (IAI), Kumar (2013) studied historical salary trends in the Indian private sector and identified macroeconomic factors that influence salary level. He also explored possible ways for future salary projections. In another project of IAI, he studied demographic and salary trends in the Indian public sector undertaking (PSU) banks and identified factors influencing long-term salary growth. The key findings and takeaways of these two projects were presented and discussed in a seminar (Kumar, 2014) of IAI[4].

Some other studies are specific to a particular liability. For example, Peethambaran (2014) provided a model for the valuation of employers' liability towards leave encashment and demonstrated variations in the liability through scenario analysis. On retirement benefits, there is a growing body of work in recent years, which broadly cover current scenarios of benefits and discuss about the challenges likely to be faced by the pension industry in the years to come.

Studies have compared the DB pension benefit plan with the DC plan. Pandit (2014) discussed about various aspects of switch over from DB plans to DC plans and pointed out that both these plans usually run parallel in an organisation, which may see some resistance from DC members on account of higher provisions being made for the DB members. The study also mentioned about the popularity of the post-retirement medical benefit scheme (PMBS) in the public sector banks (PSBs).

Elaborate discussions covering various emerging issues and challenges in the pension industry can be found in the papers of Franzen (2010) and Ramaswamy (2012). Ramaswamy (2012) discussed about sustainability of pension schemes in the falling interest rate scenario and also provided estimates of post-retirement benefits under different assumptions. Some of the recent studies (Pandit & Kandoi, 2021; Dadlani & Jain, 2022) discussed the sensitivities of assumptions used in the pension and other retirement liabilities like gratuity.

A recent paper by Sriram and Patel (2020) highlighted macro challenges in the pension sector in India and also discussed the idea to bring ERM into pensions. Sriram (2014) argued that the traditional investment strategy adopted for funding the employees benefit plans fails to assess true risk of liability, and hence, a liability driven investment (LDI) strategy could be the solution to this

---

4 The Institute of Actuaries of India has increasingly engaged in conducting various seminars such as "Capacity Building Seminar on Retirement Benefits", "Webinar on Retirement Benefits", "Global Conference of Actuaries", "India Fellowship Seminar", *etc*. The links for presentations/papers are available on its website (https://www.actuariesindia.org) covering updates on the subject including regulatory developments.

limitation. A similar argument was given in Gingrich (2015), who discussed the LDI that seeks to invest planned assets to match characteristics of the liability and mitigate the risk of declining rates on funded status. It provided current status of the US retirement benefit and the potential role of the actuary.

The European Commission in its report "Ageing Report 2012" projected various demographic parameters across select countries, and accordingly, the impact on pension liabilities due to change in the demographic profile. The report also carried out a sensitivity analysis to assess the impact on pension liability due to changes in the underlying assumptions.

The International Monetary Fund (IMF) in its publication on "Global Financial Stability Report (GFSR) - 2004" provided an informative discussion on the role of pension funds in the overall financial stability of the economy. It deliberated various accounting issues and the long-term challenges pertaining to pension funds within the overall risk management framework. In a subsequent report (GFSR, 2017), it highlighted that the employers could be transiting increasingly from DB plans to DC plans, although its pace and extent may vary across the advanced economies.

Section III
Data and Methodology

The construction of salary indices requires information on trend and growth in the salary at different points of time. As mentioned in the introductory section, salary rises because of three factors, *viz.,* inflation, real and merit. In the banking industry (including the Indian financial regulatory bodies), the wage revisions take place every five years. The latest pay revision took place in the year 2020, which is effective from November 01, 2017 to October 31, 2022. The present study uses the pay scales and structures of all the officers' cadre[5] since November 01, 1987.

The pay scales from various wage revisions of the past are sourced from the IBA website. The paper constructs wage indices for officers only and not staff and workmen, although there is availability of similar data and

---

5 The Officers' cadre covers seven scales, namely, Scale I (lowest cadre) through Scale VII (highest cadre).

6 The Bipartite on the "Conclusion of discussions between Indian Banks' Association and Workmen Unions" deals with wage settlements for the staff of the banks. The latest Bipartite settlement is the 11th, in series, which was signed on November 11, 2020.

information through various issues of Bipartite on this issue.[6] The list of banks with commonly adopted wage revisions is given in Table 1, as indicated in the latest Joint Note[7] of IBA dated November 11, 2020.

In the Indian banking sector (relating to banks as given in Table 1), the rise in salary due to inflation takes place on a quarterly basis (effective every first day of February, May, August and November of the year) in the form of dearness allowance (DA). The time series data on DA is obtained from the IBA to calculate gross salary (GS).[8] It may be mentioned that DA is a function of CPI-IW although it may not be linear[9] and of the same functional form across years.

For a fixed position, the total growth in the salary, say "g" can be decomposed into two factors by the equation:

$$(1+g) = (1+r) * (1+j),$$

Where, "r" is the real growth and "j" is the inflationary growth, respectively.

Accordingly, $r = [(1+g) / (1+j)] - 1$

For variable positions, the total growth in the salary can be decomposed into three factors by the equation:

$$(1+g) = (1+m) * (1+r) * (1+j)$$

where, "m", "r" and "j" are the merit, real and inflation - related growth, respectively.

---

7 The Joint Note on the "Conclusion of Discussions between Indian Banks' Association and Officers' Association" was also signed on November 11, 2020. The note provides various details and recommendations relating to the wage revisions applicable to a specified list of banks, wherein the wage revisions in the officer's cadre would be followed.

8 The paper considers basic pay, dearness allowance (DA), special allowance and city compensatory allowance (CCA) for the gross salary. Accordingly, other components of salary such as house rent allowance (HRA), fixed pay allowance (FPA), stagnation allowance, qualification allowances etc. are not considered, as they are largely specific to a particular cohort of employees. For example, the HRA is applicable only to those, who do not reside in banks' quarters, or qualification allowance is only applicable to those, who procure certain qualifications like Ph.D. or Certified Associate of Indian Institute of Bankers (CAIIB) *etc.*

9 The rise in the dearness allowance was largely non-linear till January 31, 2005, as the slabs for DA were not used to be neutralised till that time across the Cadres. The 100 per cent neutralization was effective w.e.f. February 01, 2005, which resulted in higher degree of linearity between the DA and CPI-IW.

Table 1: List of Banks under the umbrella of IBA
(As per Joint Note dated November 11, 2020)

Public Sector Banks	Private Sector Banks	Foreign Banks (Only Workmen)
1. Bank of Baroda	1. Federal Bank*	1. Bank of America N.A.
2. Bank of India	2. Karnataka Bank	2. Standard Chartered Bank
3. Bank of Maharashtra	3. Jammu and Kashmir Bank	3. Sonali Bank*
4. Canara Bank	4. South Indian Bank*	4. CitiBank N.A.
5. Central Bank of India	5. Karur Vysya Bank*	5. BNP Paribas
6. Indian Bank	6. RBL	6. Bank of Tokyo-Mitsubishi UFJ
7. Indian Overseas Bank	7. Nainital Bank	7. HSBC
8. Punjab and Sind Bank	8. Kotak Mahindra Bank*	
9. Punjab National bank	9. Dhanlaxmi Bank	
10. UCO Bank	10. IDBI Bank*	
11. Union Bank of India		
12. State Bank of India		

Note*: Applicable only upto Scale III.
Source: Indian Banks' Association

The first factor *viz*., merit leads to a rise in the salary, beyond inflation and in real terms, which is to reflect increasing experience, skills and expertise of the employees with the number of years of service. This takes place due to annual increments, promotions, or on acquiring specific qualifications (*viz*., Ph.D., CAIIB, *etc*.). This is in addition to the wage revisions, which largely take care of the real component of salary growth.

The compound annual growth rates (CAGR) of these three components have been derived using the above inter-relationship and are used for the construction of select salary indices to analyse the sensitivity of various actuarial assumptions to the employers' contingent liabilities[10] (covered in Section V).

[10] The paper focuses on the pension liability although other liabilities such as gratuity, leave encashment, medical assistance, *etc.* are also linked with salary indices and thus could be analysed in a similar way.

Section IV
Construction of Salary Indices

The salary index at a point of time "t" may be defined as the ratio of salary at that point of time "t" to the salary at time "0", the base year. This section deals with the construction of salary annual indices involving fixed positions. For the construction of salary annual indices, the salary for the month of November is considered rather than the 12-month average of the calendar year. This has been adopted for the indices to align them with the effective dates of wage revisions *viz.,* November 01 of every 5th year.

The starting basic pay across the cadres has increased consistently over time during the spells of five-yearly wage revisions that took place during the period 1987 to 2022 (Table 2).

The city compensatory allowance (CCA) has been considered for the locations of Area 1, as stipulated in Joint Notes of IBA. The CCA is also a

Table 2: Multipliers of Basic Pay*

Wage Revisions	Cadre						
	I	II	III	IV	V	VI	VII
01/11/1987	1.7872 (2100)	1.6767 (3060)	1.5703 (4020)	1.5453 (4520)	1.4965 (5350)	1.5455 (5950)	1.5610 (6400)
01/07/1993	2.0238 (4250)	2.0294 (6210)	2.0025 (8050)	1.9845 (8970)	1.9533 (10450)	1.9244 (11450)	1.9766 (12650)
01/04/1998	1.6706 (7100)	1.5813 (9820)	1.5578 (12540)	1.5496 (13900)	1.5445 (16140)	1.5424 (17660)	1.5289 (19340)
01/11/2002	1.4085 (10000)	1.4073 (13820)	1.4545 (18240)	1.4734 (20480)	1.4957 (24140)	1.5074 (26620)	1.5171 (29340)
01/11/2007	1.4500 (14500)	1.4038 (19400)	1.4090 (25700)	1.4941 (30600)	1.4957 (36200)	1.5778 (42000)	1.5951 (46800)
01/11/2012	1.6345 (23700)	1.6343 (31705)	1.6350 (42020)	1.6350 (50030)	1.4996 (59170)	1.6352 (68680)	1.6350 (76520)
01/11/2017	1.5190 (36000)	1.5193 (48170)	1.5193 (63840)	1.5193 (76010)	1.5192 (89890)	1.5178 (104240)	1.5175 (116120)

Note*: Multiplier of basic pay measures the relative jump in the staring basic pay in a cadre due to wage revision. It is the ratio of basic pay just after and before a wage revision. This indicates a step function in the basic salary component, which is partly due to inflation adjustment (merging DA into basic pay) and partly a discrete (step function) rise in the real salary. Figures in brackets are the starting basic pay in the respective cadres just after wage revisions.
Source: Indian Banks' Association and Author's calculations.

Table 3: City Compensatory Allowance

Wage Revisions	CCA Rates
01/11/1987	6.50 per cent of basic pay subject to a maximum of ₹220 per month
01/07/1993	4.50 per cent of basic pay subject to a maximum of ₹335 per month
01/04/1998	4.00 per cent of basic pay subject to a maximum of ₹375 per month
01/11/2002	4.00 per cent of basic pay subject to a maximum of ₹540 per month
01/11/2007	4.00 per cent of basic pay subject to a maximum of ₹540 per month
01/11/2012	4.00 per cent of basic pay subject to a maximum of ₹870 per month
01/11/2017	₹1,400 per month (fixed for all pay)

Source: Indian Banks' Association.

function of basic pay, subject to a ceiling. However, with effect from November 01, 2017, the CCA has been de-linked from the basic pay and has been fixed the same across all the basic pay levels for all the cadres (Table 3).

A new component in the salary, namely, special allowance (SA) was introduced w.e.f. November 01, 2012. This is also a function of basic pay and is counted for supernumerary benefits. The structure is provided in Table 4.

The gross pay has increased consistently across the cadres during the period 1987 to 2022. The salary indices are constructed for all the cadres. On an average, the pay appeared to have increased by around 23 times in these 35 years. For example, the salary index for Scale I has increased from a base of 100 (base year 1987) to 2,291 in the year 2022.

Table 4: Structure of Special Pay

Cadre	Wage Revisions	
	01/11/2012	01/11/2017
I to III	7.75 per cent of basic pay and applicable DA thereon	16.40 per cent of basic pay and applicable DA thereon
IV to V	10.00 per cent of basic pay and applicable DA thereon	19.00 per cent of basic pay and applicable DA thereon
VI to VII	11.00 per cent of basic pay and applicable DA thereon	20.00 per cent of basic pay and applicable DA thereon

Source: Indian Banks' Association.

The lowest rise was seen in the case of Scale II, which witnessed a 21-fold increase, while the highest was in case of Scale VII (by about 25-fold). It may be noted that the variations in growth have been quite low, indicating quite comparable growth in pay across the cadres. Overall, two cadres (Scale II and III) witnessed a slightly lower than 22-fold increase over the 35-year period, while other five cadres witnessed a rise of more than 22-fold in their respective salaries during the same period.

The simple average of salary indices of all the seven scales are also constructed and presented in Chart 1H. The charts exhibit high degree of similarity in the indices across the scale. Further, the two-parameter exponential curve, of the form y = a * exp (bx), is found to be appropriate in explaining the salary escalation during the period of study.

While the overall resemblance of indices across a long period of 35 years is apparent from the above charts, the compound annual growth rates

Chart 1: Salary Indices for various Scales *(Contd.)*

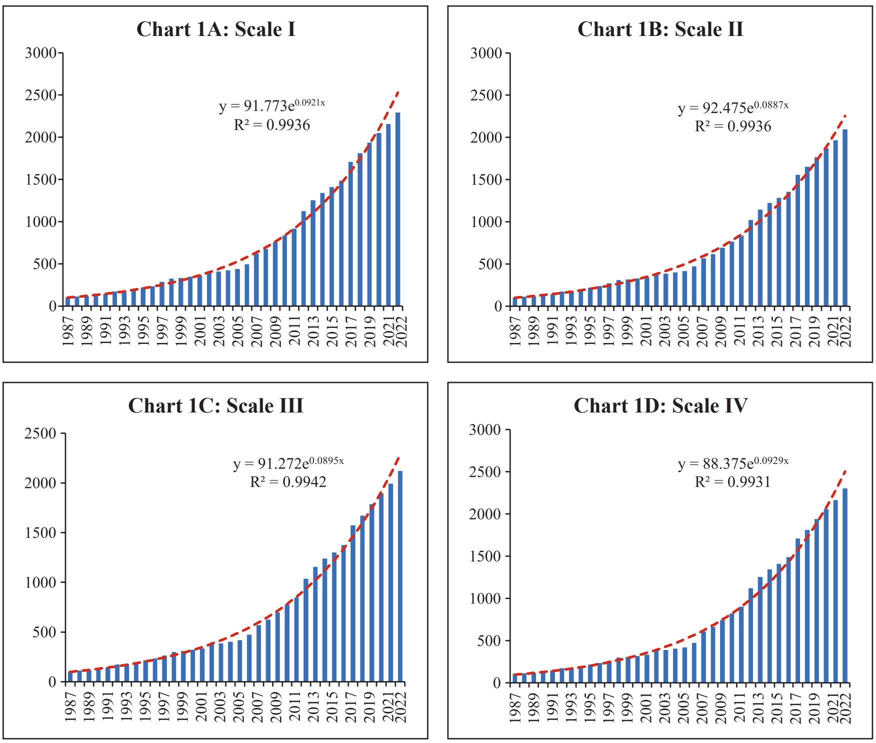
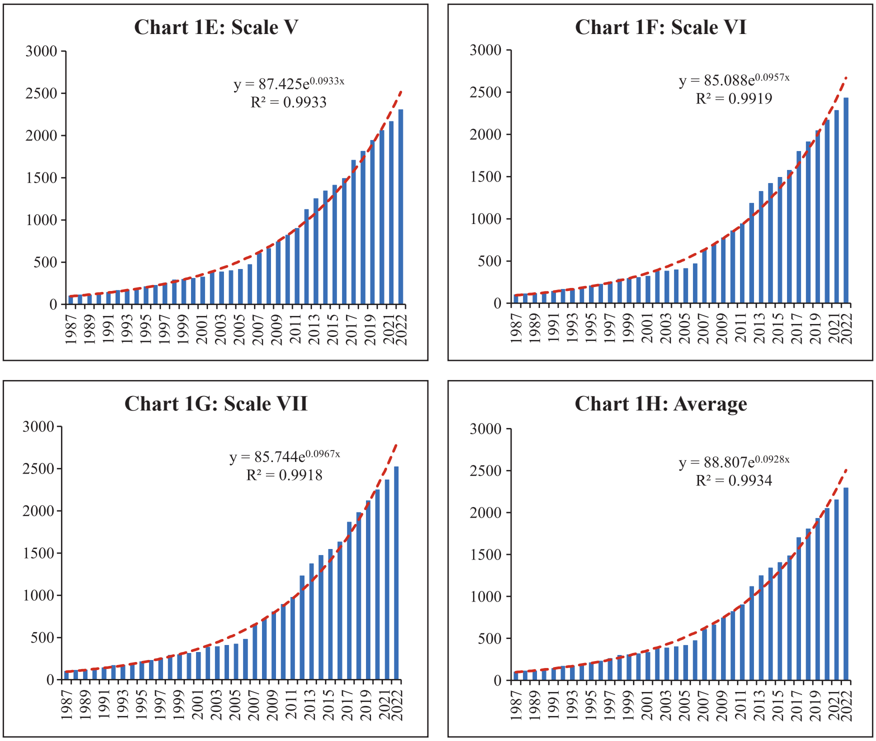


Chart 1: Salary Indices for various Scales *(Concld.)*



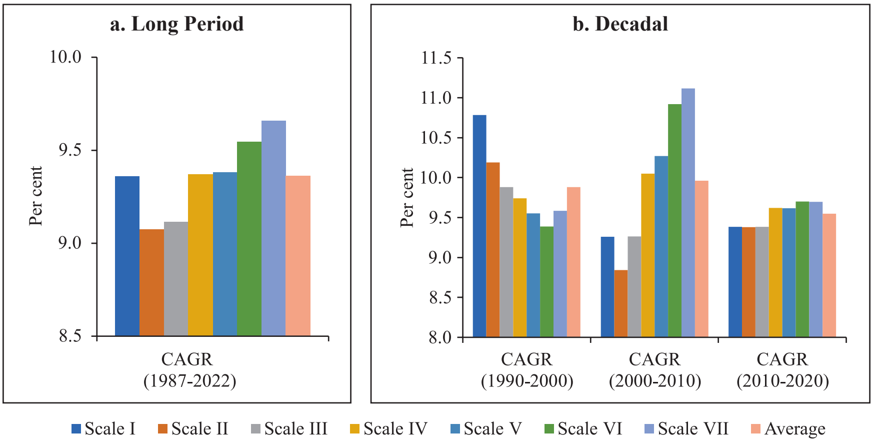
Source: Author's calculations.

(CAGRs) of the indices over a shorter time horizon are also plotted, which reveal interesting findings (Chart 2).

The salary escalation appeared to be the highest in Scale I during the decade of 1990-2000. In the subsequent decade *viz.,* 2000-2010, the salary of Scale VI and Scale VII appeared to escalate at a higher rate than that of other scales. It may be interesting to note that no scale witnessed a consistently higher or lower growth than others, which led to a similar growth rate (in terms of CAGR) in the longer run. This also indicates that a particular scale may not remain at an advantageous or disadvantageous position across various spells of wage revisions.

The salary indices are projected for future 18 years *viz.,* 2023 to 2040 under two assumptions. The first assumption uses the long-term CAGR (Scale-wise) during the 35 years to estimate the annual indices for the future.

Chart 2: Cadre-wise Salary - CAGR



Source: Author's calculations.

The second assumption uses the fitted parameters of the exponential curve to forecast future annual indices.

The projection of future annual indices under these two assumptions provides a similar profile, which strengthens the reliability of the estimates (Tables 5 and 6).

Table 5: Projections of Annual Salary Indices during 2023-2040
(Under Assumption 1)

Year	Scale I	Scale II	Scale III	Scale IV	Scale V	Scale VI	Scale VII	Average
2023	2505.17	2280.83	2310.96	2514.05	2523.45	2662.77	2764.22	2508.64
2024	2739.64	2487.81	2521.59	2749.62	2760.19	2916.93	3031.21	2743.54
2025	2996.06	2713.58	2751.43	3007.27	3019.14	3195.36	3323.99	3000.44
2026	3276.48	2959.83	3002.21	3289.06	3302.39	3500.35	3645.05	3281.39
2027	3583.14	3228.44	3275.85	3597.25	3612.20	3834.46	3997.12	3588.65
2028	3918.50	3521.41	3574.44	3934.33	3951.09	4200.46	4383.20	3924.68
2029	4285.25	3840.98	3900.23	4302.98	4321.76	4601.40	4806.57	4292.17
2030	4686.33	4189.54	4255.73	4706.19	4727.21	5040.60	5270.83	4694.08
2031	5124.95	4569.74	4643.62	5147.17	5170.70	5521.73	5779.93	5133.62
2032	5604.62	4984.44	5066.87	5629.47	5655.79	6048.78	6338.20	5614.32
2033	6129.19	5436.77	5528.70	6156.97	6186.40	6626.14	6950.40	6140.03
2034	6702.85	5930.15	6032.62	6733.89	6766.78	7258.60	7621.73	6714.96
2035	7330.21	6468.30	6582.48	7364.88	7401.61	7951.43	8357.90	7343.73
2036	8016.28	7055.30	7182.45	8054.98	8096.01	8710.40	9165.17	8031.38
2037	8766.56	7695.56	7837.10	8809.76	8855.54	9541.81	10050.43	8783.42
2038	9587.07	8393.92	8551.43	9635.26	9686.33	10452.58	11021.18	9605.87
2039	10484.37	9155.66	9330.86	10538.11	10595.07	11450.28	12085.70	10505.34
2040	11465.66	9986.53	10181.34	11525.55	11589.05	12543.21	13253.04	11489.03

Source: Author's calculations.

Table 6: Projections of Annual Salary Indices during 2023-2040
(Under Assumption 2)

Year	Scale I	Scale II	Scale III	Scale IV	Scale V	Scale VI	Scale VII	Average
2023	2527.33	2253.27	2288.94	2504.86	2513.88	2667.47	2786.57	2508.06
2024	2771.15	2462.27	2503.25	2748.72	2759.71	2935.36	3069.49	2751.95
2025	3038.50	2690.65	2737.62	3016.31	3029.59	3230.16	3381.13	3019.56
2026	3331.63	2940.22	2993.94	3309.95	3325.85	3554.56	3724.42	3313.19
2027	3653.05	3212.93	3274.25	3632.18	3651.09	3911.54	4102.56	3635.37
2028	4005.48	3510.94	3580.81	3985.78	4008.13	4304.37	4519.09	3988.88
2029	4391.90	3836.59	3916.07	4373.81	4400.09	4736.65	4977.91	4376.77
2030	4815.61	4192.44	4282.72	4799.61	4830.38	5212.35	5483.32	4802.37
2031	5280.19	4581.30	4683.70	5266.86	5302.75	5735.82	6040.04	5269.37
2032	5789.60	5006.23	5122.22	5779.60	5821.31	6311.86	6653.29	5781.77
2033	6348.15	5470.57	5601.80	6342.25	6390.59	6945.76	7328.79	6344.00
2034	6960.58	5977.98	6126.29	6959.68	7015.53	7643.31	8072.88	6960.91
2035	7632.10	6532.46	6699.87	7637.22	7701.58	8410.92	8892.52	7637.80
2036	8368.40	7138.36	7327.17	8380.72	8454.73	9255.62	9795.38	8380.52
2037	9175.74	7800.46	8013.19	9196.60	9281.53	10185.15	10789.90	9195.46
2038	10060.96	8523.98	8763.44	10091.91	10189.18	11208.03	11885.40	10089.65
2039	11031.59	9314.60	9583.94	11074.37	11185.59	12333.64	13092.12	11070.79
2040	12095.86	10178.56	10481.26	12152.49	12279.44	13572.30	14421.37	12147.34

Source: Author's calculations.

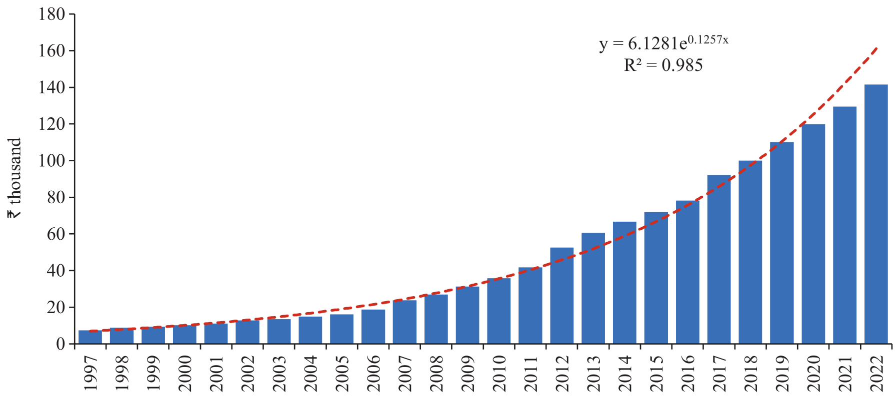
The projections of salary indices under assumption 2 (through exponential curve) yields slightly higher estimates than those under assumption 1 (through CAGR). However, it may be noted that the projections from these two approaches are quite comparable.

The above projections may be useful for various long-term macroeconomic analysis, wherein these projections can be used as a critical (exogenous) input. This may also provide a reasonable understanding to the employees of the banks in their future planning and budgeting.

Section V
Valuation of Employers' Liabilities

The above constructed salary indices provide useful insights into the future salary projections for every fixed position. As indicated earlier, these indices do not take care of the merit (promotional) component of the salary. An attempt is made to construct the salary indices for varying positions. For this, the case of Scale I is considered with the base year 1997. Accordingly, the expected salary of a newly recruited officer in Scale 1, who joins the bank on November 01, 1997 is considered and it is assumed that the officer is promoted every

Chart 3: Salary (with Merit)



Source: Author's calculations.

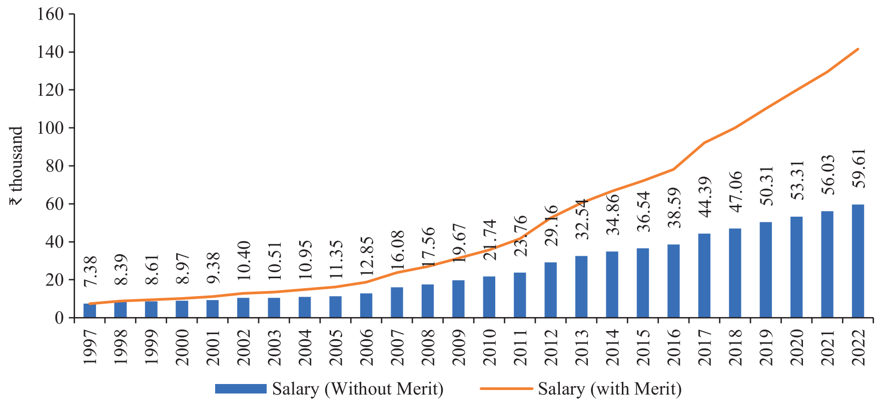
seven years[11] after joining. That is, the promotions to Scale II on November 01, 2004, Scale III on November 01, 2011, and to Scale IV on November 01, 2018 are assumed. This is in addition to the regular annual increments applicable every November. With this set of assumptions, the expected salary escalation is derived along with an exponential fitting (Chart 3).

It is important to note that the CAGR of the salary index (with merit) during the 25 year-period from 1997 to 2022 of the stated case is 12.54 per cent. The same without considering merit for the study period is 8.71 per cent. This indicates that 3.52 per cent [100*(1.1254/1.0871)-1] average annual rise in the salary was contributed by merit during the period.

Interestingly, the relative salary of the new recruits who joined on November 01, 1997 and November 01, 2022 was around ₹7.4 thousand and around ₹59.6 thousand, respectively. However, salary of the new recruits, who joined on November 01, 1997, was ₹141.5 thousand (as on November 01, 2022) under the specified assumptions about promotion, *etc*., as indicated earlier. It may also be noted that the shape of the exponential curve changes significantly in case of merit, which is steeper, as compared to the one without merit (Chart 4).

[11] In the absence of historical data on promotion timings, the assumption of promotions at every seven years is made to reflect a generic realistic scenario (four promotions in a service life of 28-30 years, although they may not be equally spaced).

Chart 4: Salary Comparison



Source: Institute of Actuarial of India and Author's calculations.

The paper considers a hypothetical cohort of one lakh officers (all aged exactly 27 years as on November 01, 1997), who joined the bank on this date in Scale I. The promotion profile of these officers is assumed to be identical, which was used for constructing the merit salary index. It may be noted that many of these officers may leave the organisation, while some others may die and some may take voluntary retirement before their date of normal retirement (on attaining age of 60 years) *viz.,* October 31, 2030 (same for all in the cohort).

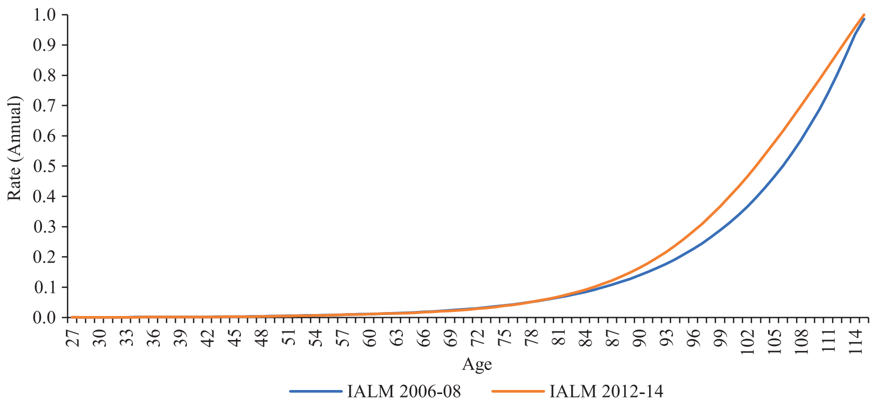
V.1 Multiple Decrements

The paper attempts to estimate these possible exits (either through attrition, or death or early retirement) and remaining through normal retirement. Accordingly, we take three decrements into account in this case, which are (1) Mortality (2) Attrition (including early retirement) and (3) Retirement. The other decrements, such as "ill-health retirement", are ignored.

Regarding the first decrement of mortality, it is assumed that all officers of the aforementioned cohort follow "Indian Assured Lives Mortality Table 2012-14 Ultimate".[12] The previous two such life tables were "IALM 1994-96

[12] This mortality table is the latest published life table, published by the Institute of Actuaries of India (IAI) with concurrence of the Insurance Regulatory and Development Authority of India (IRDAI) and is effective from April 01, 2019. The paper considers this mortality table to reflect the future likely survival rates of the officers of the banks in a better manner.

Chart 5: Mortality Rate



Source: Author's calculations.

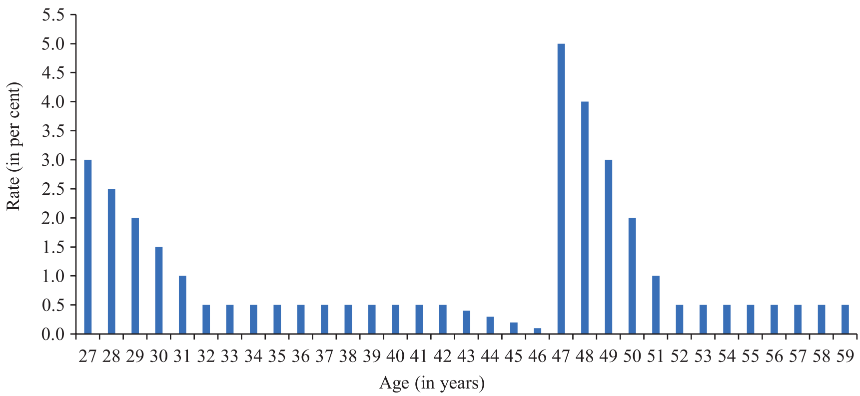
(Modified) Ultimate" and "IALM 2006-08 Ultimate", which were effective from January 1, 2005 and April 1, 2013, respectively.

As the life profile of the officers is from 1997 to 2030 (pre-retirement) and 2030 onwards (post-retirement) would impact the pension liability, the latest IALM has been considered in this case. A better approach could be to use all tables with their respective applicable periods. However, this may make the computations more complicated. A comparative study of latest two mortality tables indicates that the mortality profile has changed noticeably at old ages (above 80 years). This underscores the need to use IALM Table 2012-14 for a better reflection of the futuristic mortality of the cohort (Chart 5).

For the second decrement of attrition, it is assumed that the cohort follows an attrition rate as provided in Chart 6. The attrition rate is a crucial input parameter for valuation of such long-term liability, and the rate is unlikely to be smooth.

Our assumption on this rate is based on the fact that the attrition rate should be higher during initial periods of service. Chart 6 exhibits that the attrition rate tapers off since joining over the period of five years from a starting rate of 3 per cent per annum and remains stagnant at 0.5 per cent for about a decade. As quitting before 20 years of service does not result in any payout towards pension under the DB plan, it is disadvantageous for those

Chart 6: Assumption on Attrition Rate[13]



Source: Author's calculations.

who quit ahead of 20 years after reaching closer to it. Accordingly, a further tapering off in the rates is assumed till 20 years.

After reaching the point of eligibility for the pension, the attrition results in the eligibility towards pension. Accordingly, the attrition rates beyond this point are indeed the (voluntary/early) retirement rates. It may be mentioned that the attrition rates correspond to "resignations", while the retirement rates correspond to "early retirement" instead of resignations.

There is a sharp increase in the retirement rate at 20 years of service, which makes an employee eligible to take early retirement. We assume this rate to be at 5 per cent. Again, from this point of time, the retirement rate should show a declining trend, which is reflected in the Chart. After a few years, the rate would dip to its long-run average value of 0.5 per cent.

With the above assumptions on the mortality and attrition rates, an attempt is made to carry out valuation of retirement benefits using the hypothetical cohort, as discussed earlier. For these, both plans (DC and DB) are considered, as both are running simultaneously in the banks. Further, there are some additional benefits, such as gratuity (involving a one-time lump-sum

[13] The attrition rate for the public sector banks was assessed to be at around 0.50 per cent, as per Saha (2013). The rate for the private and foreign banks are likely to differ from this average and is likely to be on an upper side. The sensitivity of different attrition rate assumptions is analysed in the latter part of the paper, which provide possible impact and implications on the pension liability.

payment) which will typically remain applicable for both the plans and would be linked to the number of years of service and the latest pay drawn ahead of retirement/other forms of exit.

V.2 Demographic and Contribution Functions

We now define some of the actuarial notations as below:

x = age of the employee

l_x = size of the cohort of the employees at age x

q_x = mortality rate, *i.e.,* the probability that the employee aged x years will die before (x+1) years of age

w_x = the attrition rate (or, the withdrawal rate) per annum at age x

r_x = retirement rate per annum at age x.

N_d = number of deaths during the year from age x to age x+1

N_w = number of attrition (withdrawals/resignations) during the year from age x to age x+1 before early retirement age (ERA)

N_r = number of attrition (early retirements) during the year from age x to age x+1 on or after ERA but before normal retirement age (NRA)

$N_T = N_d+N_w+N_r$ = total number of exits per annum from age x to age x+1

$l_{x+1} = l_x * [1 – (N_d+N_w+N_r)] = l_x * [1 – (N_T)]$

s_x = salary function (can be derived as salary indices)

The base year function s_{27} = 1.0000, in the present case

i = annual effective interest rate

v = discounting factor = 1 / (1+i)

$D_x = l_x * v^x$

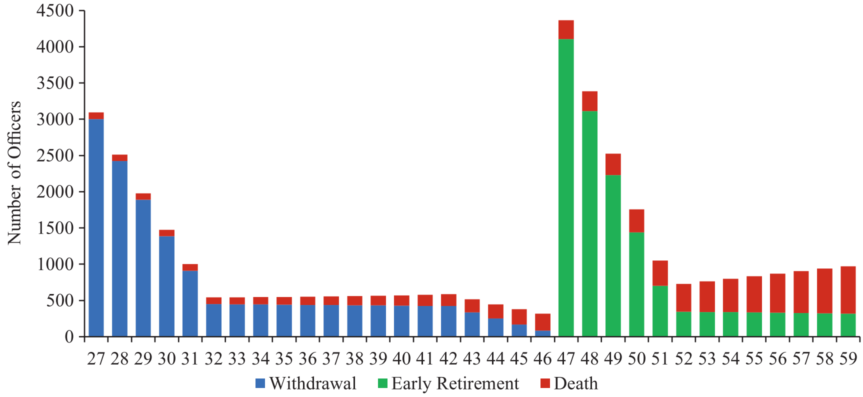
$N_x = \sum D_x$

${}^sD_x = s_x * D_x$

${}^sN_x = \sum {}^sD_x = \sum (s_x * D_x)$

With the given assumptions on mortality and attrition rates, the hypothetical cohort of one lakh officers (all aged exactly 27 years on their joining on November 01, 1997 at the beginning of Scale I) is tracked through the multiple decrement life table. The initial phases are led by exits through

Chart 7: Exits from Cohort



Source: Author's calculations.

quitting (applicable during age 27-46 years) the organisation. A sudden rise in early retirements (applicable during age 47-59 years) is apparent, which tapers off subsequently. It is remarkable to note that the number of deaths of officers increases over the period despite reducing the base each year (Chart 7).

Under the given assumptions, out of one lakh officers, there is an overall attrition of 29,471 officers because of resignations (15,234 cases) and early retirement (14,237 cases). With the expected number of deaths of 8,296, the remaining 62,233 officers (62.2 per cent) shall be expected to retire.

Before constructing various contribution and retirement benefit functions, an attempt is made to compute the actuarial present value (APV) of the payouts towards the salary disbursements of officers, likely to be drawn during the period of service. The APV is a much complex function as compared to the usual present value of certain cash flows (certainty, in terms of known amount and known timing). Indeed, the profile of number of resignations, early retirements and deaths are basic input to the APV. The APV is computed for a series of contingent cash flows, wherein the cashflows depend on some contingent event(s) like death or survival of officer during a period. Accordingly, APV itself is a random variable following a statistical distribution with expected mean of APV and variance of APV.

Using the salary index (with merit) of the gross salary (as derived from Chart 3) and its projected values for future years using a CAGR of 12.50 per cent, round number derived from Assumption 2, as stated earlier, the APV of the aggregate salary is computed for the group/cohort of officers as per the additional assumptions given below:

A constant interest rate of 8 per cent[14] per annum is assumed for the entire period. With this set of assumptions, the APV of the salary is computed and is given in Table 7.

Table 7: Actuarial Present Value of Aggregate Salary of the Cohort (Contribution Function)

Col 1	Col 2	Col 3	Col 4	Col 5	Col 6	Col 7	Col 8	Col 9
x	q_x	w_x	r_x	l_x	s_x	D_x	${}^sD_x$	${}^sN_x$
27	**0.000934**	**0.0300**		**100000**	**1.0000**	**92593**	**92593**	**5098263**
28	0.000942	0.0250		96907	1.1895	83082	98824	5005670
29	0.000956	0.0200		94393	1.2752	74932	95552	4906847
30	0.000977	0.0150		92415	1.3840	67927	94010	4811294
31	0.001005	0.0100		90938	1.5046	61891	93124	4717285
32	0.001042	0.0050		89937	1.7394	56676	98584	4624161
33	0.001086	0.0050		89394	1.8236	52160	95120	4525577
34	0.001140	0.0050		88850	2.0203	48003	96980	4430456
35	0.001202	0.0050		88304	2.1874	44174	96627	4333477
36	0.001275	0.0050		87757	2.5463	40648	103504	4236849
37	0.001358	0.0050		87206	3.2235	37401	120563	4133345
38	0.001453	0.0050		86651	3.6505	34411	125614	4012782
39	0.001560	0.0050		86092	4.2368	31656	134119	3887168
40	0.001680	0.0050		85528	4.8448	29119	141076	3753049
41	0.001815	0.0050		84956	5.6471	26782	151241	3611973
42	0.001969	0.0050		84377	7.1236	24629	175446	3460733
43	0.002144	0.0040		83789	8.1952	22646	185586	3285287
44	0.002345	0.0030		83274	9.0424	20839	188438	3099701
45	0.002579	0.0020		82829	9.7520	19193	187166	2911263
46	0.002851	0.0010		82450	10.5861	17690	187263	2724097
47	**0.003168**		**0.0500**	**82133**	**12.4820**	**16316**	**203658**	**2536834**
48	0.003536		0.0400	77766	13.5476	14304	193788	2333176
49	0.003958		0.0300	74380	14.9086	12668	188864	2139388
50	0.004436		0.0200	71854	16.2424	11331	184049	1950525
51	0.004969		0.0100	70098	17.5424	10236	179557	1766475
52	0.005550		0.0050	69049	19.1652	9336	178918	1586918
53	0.006174		0.0050	68321	21.5608	8553	184406	1408000
54	0.006831		0.0050	67557	24.2559	7831	189944	1223594
55	0.007513		0.0050	66758	27.2879	7165	195517	1033650
56	0.008212		0.0050	65923	30.6989	6551	201115	838133
57	0.008925		0.0050	65052	34.5362	5986	206727	637018
58	0.009651		0.0050	64146	38.8533	5465	212342	430291
59	0.010393		0.0050	63206	43.7099	4986	217949	217949
60				**62233**		**4546**		

Source: Author's calculations.

[14] A constant interest rate of 8 per cent is assumed for the study because of the nature of liability, which is a long-term. Accordingly, a baseline assumption is made and sensitivity is assessed if we depart from this baseline.

From Table 7, it is observed that the cohort of one lakh officers, who joined in 1997 at an annual gross salary of ₹1 per annum each (total salary ₹1 lakh per annum for the cohort), is expected to result in an APV of around ₹50.98 lakh towards aggregate salary disbursements to the cohort for all the years together. Accordingly, the APV per person is ₹50.98. The annual salary of the last year ahead of retirement (at NRA) is expected to be ₹43.71 (more than 43 times compared to the salary of ₹1 at joining).

In an extreme case, if we assume that all one lakh officers remain in the bank till normal retirement age (*i.e.,* no one quits or takes early retirement or dies), then the APV of the aggregate salary would be around ₹66.08 lakh. In such an extreme scenario, the aggregate salary will be around ₹397.76 lakh (in nominal terms, *i.e.*, without discounting for time value of money). This equates to the APV of the aggregate salary of the cohort under the assumption of interest rate = 0 together with no withdrawal/death etc.

It may be mentioned that many benefits are functions of the pay (could be just basic pay or with add-ons such as special pay, DA *etc*.). For example, a contribution (say, towards provident fund) could be "y" per cent of the pay. In case, the value of "y" remains the same throughout the period, the contribution functions will be the same whether it is for contribution (PF) or is for the pay itself. Further, the APV of the contributions (say, amounts deposited in the PF) will also be "y" per cent of the APV of the pay. However, withdrawals, such as from PF, at some point(s) of time may complicate the equation, and hence may require necessary adjustments.

V.3 Age Retirement Function

The computations for the retirement benefits are attempted in a similar manner. It may be mentioned that this long-term liability of the organisation is quite different from a DC plan, as covered in Table 7. The nature of this liability is contingent, as no pension is admissible for quitting the job before completing 20 years of service in the organisation. Accordingly, continuing with the same illustration of the characteristics of the cohort, the APV of pension liability is simply 'zero' for those who exit from the organisation prior to November 01, 2017 (the assumptions of the hypothetical cohort are taken as the same as in the previous case of demonstration carried out for the contribution function).

The computation of retirement functions requires the life annuity function. The usual annuity (certain annuity) is the present value of a series of future payments for a fixed period at the rate of unit currency of payment per annum. The life annuities are more complicated annuities, which do not have a fixed period and continue till the death of the annuitant.

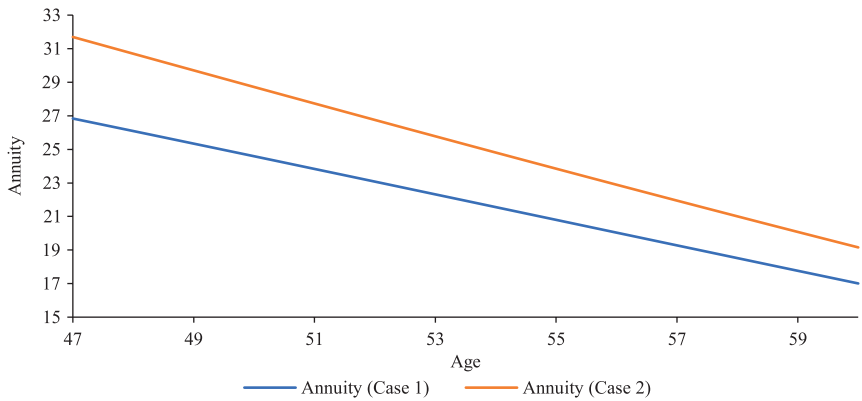
The pension amount is linked with the basic pay directly, as long as the officer is in service. At the time of retirement (or, early retirement), the initial (starting) pensionable amount is fixed as half of the basic pay plus other applicable pay components, as prevalent just prior to the retirement. However, once this amount is fixed and the officer has already retired, this amount does not track the future basic pay, which will only be available to those who are active in the service. Accordingly, we cannot expect the pension amount to grow with the CAGR of salary (12.50 per cent in our case). After retirement, the pension is largely expected to grow by a rate slightly above the inflation rate, as pension tracks dearness allowance and that is linked with the inflation rate. There will be a minor raise due to subsequent wage revisions though after retirement.

With the above points, the CAGR of pension is assumed to be 7 per cent, which is higher than the observed CAGR of CPI-IW inflation[15] as witnessed during the recent years. Using an interest rate of 8 per cent and pension escalation rate of 7 per cent, a net effective actuarial annual discount rate (v) is computed as 0.9907. Using this net discount rate, the annuity (Case 1) is computed.

A different scenario (Case 2) is also considered. Case 2 pertains to the zero net effective actuarial interest rate, *i.e.*, unit discount rate, v = 1 (assuming same rate of pension growth and interest rate). However, the same (Case 2) is not used in the subsequent calculations. The life annuities are computed for each year of possible retirements (x = 47 to 60 years) and are provided in Chart 8 (details are provided in Table A1 in Annex).

[15] The CAGR of CPI-IW inflation rate was slightly below 7 per cent during 15 years (2001-16) at the base year 2001, and dipped to around 4.4 per cent during the subsequent 6 years (2016-22) at the base year 2016.

Chart 8: Annuity Function



Source: Author's calculations.

It may be seen that the annuity differentials under these two cases, narrow down consistently with the increase of the age. The annuities are calculated at the end of the year, that is, in arrear.

The retirement functions are now constructed and provided in Table 8. Under the underlying set of assumptions on decrements, out of the one lakh officers who joined the organisation, on an expected term, 8,296 officers will die during their service period, of which, 2,633 will die before age 47 years, so will not be able to take any pension. The remaining, 5,663 will die during age 47-60 years, leading to some applicable pension to their respective families.

Accordingly, a total of 15,234 will be quitting without taking any pension coupled with 2,633 dying without taking any pension. Remaining 82,133 will have either lead to some pension or family pension, of which, 62,233 will survive at least till retirement.

The aggregate pension liability of the cohort is estimated at ₹114.01 lakh as in year 2017 (starting point of pension disbursement). Discounting it back to the time of joining in 1997 gives an estimate of ₹24.46 lakh assuming an interest rate of 8 per cent for discounting. The estimations are based on the rule that the retirees will get pension at half of their pay, which would be applicable at the time of their retirements.

Table 8: Age Retirement Functions

Col 1	Col 2	Col 3	Col 4	Col 5	Col 6	Col 7	Col 8	Col 9	Col 10	Col 11	Col 12	Col 13	Col 14
X	l_x	q_x	N_d	w_x	N_w	r_x	N_r	N_T	0.50 * s_x	a_x	(10)* (11)	(8)*(12) (in lakh)	PV of (13)
27	**100000**	**0.000934**	**93**	**0.0300**	**3000**		**0**	**3093**					**24.4601**
28	96907	0.000942	91	0.0250	2423		0	2514					
29	94393	0.000956	90	0.0200	1888		0	1978					
30	92415	0.000977	90	0.0150	1386		0	1477					
31	90938	0.001005	91	0.0100	909		0	1001					
32	89937	0.001042	94	0.0050	450		0	543					
33	89394	0.001086	97	0.0050	447		0	544					
34	88850	0.001140	101	0.0050	444		0	546					
35	88304	0.001202	106	0.0050	442		0	548					
36	87757	0.001275	112	0.0050	439		0	551					
37	87206	0.001358	118	0.0050	436		0	554					
38	86651	0.001453	126	0.0050	433		0	559					
39	86092	0.001560	134	0.0050	430		0	565					
40	85528	0.001680	144	0.0050	428		0	571					
41	84956	0.001815	154	0.0050	425		0	579					
42	84377	0.001969	166	0.0050	422		0	588					
43	83789	0.002144	180	0.0040	335		0	515					
44	83274	0.002345	195	0.0030	250		0	445					
45	82829	0.002579	214	0.0020	166		0	379					
46	82450	0.002851	235	0.0010	82		0	318					
47	**82133**	**0.003168**	**260**		**0**	**0.0500**	**4107**	**4367**	**6.2410**	**26.8372**	**167.49**	**6.8782**	**6.8782**
48	77766	0.003536	275		0	0.0400	3111	3386	6.7738	26.0911	176.74	5.4976	5.0904
49	74380	0.003958	294		0	0.0300	2231	2526	7.4543	25.3417	188.90	4.2152	3.6139
50	71854	0.004436	319		0	0.0200	1437	1756	8.1212	24.5891	199.69	2.8698	2.2781
51	70098	0.004969	348		0	0.0100	701	1049	8.7712	23.8340	209.05	1.4654	1.0771
52	69049	0.005550	383		0	0.0050	345	728	9.5826	23.0766	221.13	0.7635	0.5196
53	68321	0.006174	422		0	0.0050	342	763	10.7804	22.3176	240.59	0.8219	0.5179
54	67557	0.006831	461		0	0.0050	338	799	12.1280	21.5576	261.45	0.8831	0.5153
55	66758	0.007513	502		0	0.0050	334	835	13.6439	20.7970	283.75	0.9471	0.5117
56	65923	0.008212	541		0	0.0050	330	871	15.3494	20.0366	307.55	1.0137	0.5071
57	65052	0.008925	581		0	0.0050	325	906	17.2681	19.2769	332.88	1.0827	0.5015
58	64146	0.009651	619		0	0.0050	321	940	19.4266	18.5186	359.75	1.1538	0.4949
59	63206	0.010393	657		0	0.0050	316	973	21.8550	17.7622	388.19	1.2268	0.4872
60	**62233**		**0**		**0**		**62233**	**62233**	**23.3848**	**17.0084**	**397.74**	**247.5251**	**91.0145**
			8296		**15234**		**76470**	**100000**				**276.3440**	**114.0074**

Source: Author's calculations.

All the computations in this section regarding contribution and retirement functions are carried out to provide expected values of these liabilities and need to be interpreted in actuarial and statistical sense. The estimates are further based on the underlying set of assumptions.

Accordingly, changes in the set of assumptions will lead to corresponding changes in the liability profile of an employer. The computations are complex requiring a lot of assumptions to be made and many other factors may need to be either ignored or approximated.

V.4 DB versus DC Plan – A Comparison

From Tables 7 and 8, the relative cost of pension liability to the employer is assessed. The banks needed to contribute 10 per cent (got revised to 14 per cent in 2021) of the salary towards DC. For the underlying cohort, we computed APV of the aggregate salary as ₹50.98 lakh *i.e.,* ₹50.98 per officer (Table 7). Accordingly, the APV of the contribution would also be 10 per cent for the past years and 14 per cent since 2021. This leads to an expected APV for this cohort to be in the range of ₹5.10 to ₹7.14. In any case, this is substantially lower as compared to the APV of DB pension outgo (Table 8) at ₹24.46. This indicates that the cost of the DB pension plan could be 3 to 5 times higher than that of the cost of DC pension plan under the underlying set of assumptions.

The significantly higher cost of the DB plan to the banks may taper with the passage of time, as the number of employees on the payroll with DB plan would diminish over time and the number of employees with DC plan would rise with the adoption of DC plans by banks.

V.5 Sensitivity of Assumptions - Scenarios

An attempt is made in this section to assess how the APV will deviate from its expected value to align with the revised expected value on account of the corresponding change in the assumptions. The actual realisation on various assumptions could, of course, be quite different from its assumed value. The discussion in the previous section was based on several assumptions. Following this discussion, an attempt is made to assess their marginal impact on liability, which are carried out through scenario analysis.

However, the analysis requires revisiting assumptions regarding (1) Mortality rate (2) Attrition rate (2) Retirement rate (3) Interest rate (4) Inflation rate, and (5) Salary growth rate. Firstly, their marginal impacts on pension liability are considered.

Mortality Rate

The mortality, attrition and retirement rates are the decrements, which do not impact the pension liability directly. Various combinations of these three decrements lead to different composition of the residual cohort at different points of time. The higher decrement rates will squeeze the cohort sooner and *vice-versa*. Further, a lower/higher rate of one decrement also impacts the loss of life (due to mortality) and exit (due to attrition/early retirement/retirement) together. Indeed, all three are inter-related impacting each other.

As noted, the mortality rates are assumed to follow the "Indian Assured Lives Mortality Table 2012-14 Ultimate". Although this may be the best available choice for the current study, it may be appreciated that the officers join the organisation after passing through some base level medical checks. Accordingly, their lives, at the time of joining, are not "Ultimate" but rather "Select". The Select lives are expected to have lower mortality rates than Ultimate lives, especially during the initial years. One way to incorporate it could be through some demographic assumptions. However, no attempt is made for this here. Instead, two different scenarios are taken: the mortality rates at each age are ± 10 per cent (higher/lower) than the earlier assumed rates. That is,

Case 1: $q'_x = 1.10 * q_x$ for all x

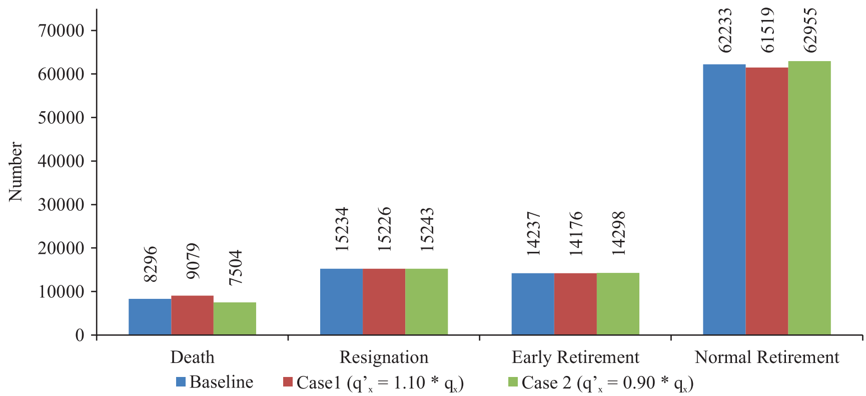
Case 2: $q'_x = 0.90 * q_x$ for all x

The impact on this change in mortality (keeping all other assumptions unchanged) leads to a different composition of cohort as exhibited in Chart 9.

From the Chart 9, it is observed that the change in mortality will impact the exits as well as early retirements the least. However, it will impact (inversely) the normal retirements with a corresponding change of around ± 1 per cent. The higher mortality leads to lesser number of normal retirements.

The impact of change in mortality on pension liabilities is worked out and is provided in Chart 10. There is a negative association between mortality

Chart 9: Mortality Shift- Impact on Pension Liability



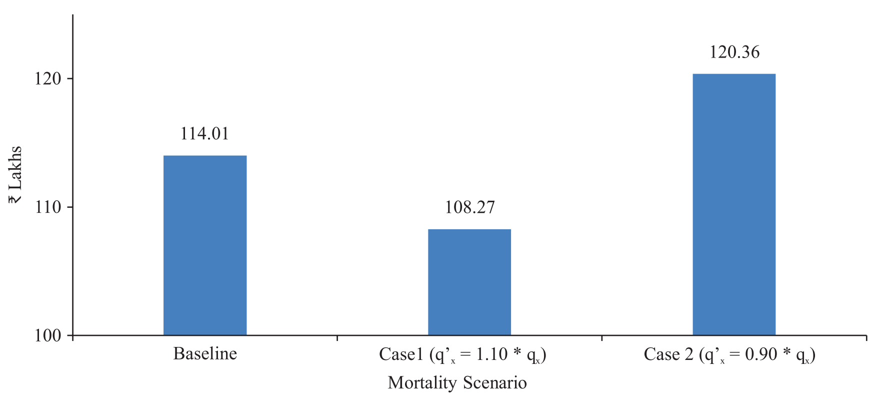
Source: Author's calculations.

and APV of pension liabilities. Higher mortality leads to lower APV of the pension liability. Further, the Chart exhibits that a change in mortality by 10 per cent (increase/decrease) translates into a change of around 5 per cent (decrease / increase) in the APV, keeping other factors unchanged.

Attrition and Retirement Rates

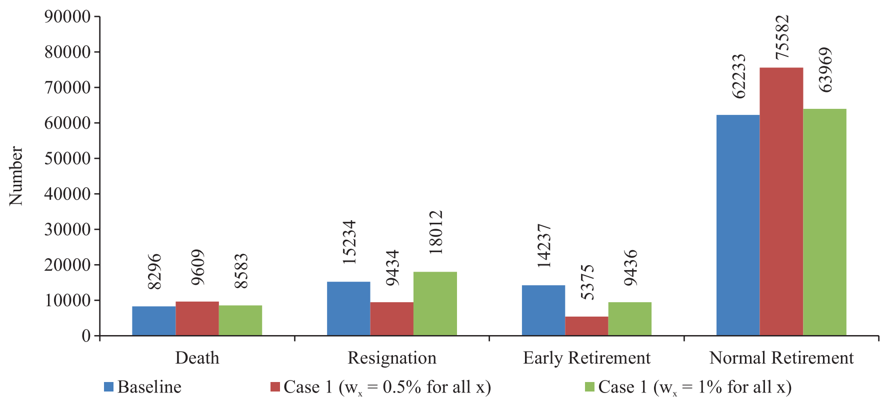
The attrition rates are assumed as step functions in this paper (Chart 6). An attempt is made to assess the impact on the cohort profile and the pension liability due to variations in the attrition rates. This is done by changing the

Chart 10: Mortality Shift – Demographic Impact on Cohort



Source: Author's calculations.

Chart 11: Attrition Shift- Demographic Impact on Cohort



Source: Author's calculations.

assumption of attrition rate as a constant equal to 0.5 per cent per annum (Case 1) and 1 per cent per annum (Case 2) across the entire service period. This way, we assume same decrement rates for "exits" and "early retirements" within each case. Chart 11 shows the cohort profile under the two scenarios along with the earlier assumed variable attrition rates.

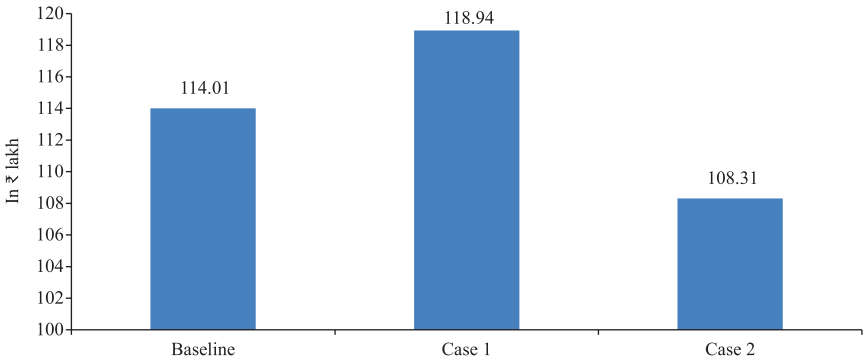
It is observed that the assumed attrition rates, varying by age within a wide range of 0.1 per cent to 5.0 per cent per annum across ages have a weighted impact on cohort somewhere in between the two scenarios. Further, the cohort is impacted more significantly than the scenarios of mortality, which was changed by ± 10 per cent (Chart 11).

Now, the impacts are depicted in Chart 12. The two scenarios lead to a change in the APV of liability by +4.32 per cent and -5.00 per cent, respectively. This shows that the existing assumption of varying attrition rate leads to an overall impact somewhere in between a scenario of constant rate of 0.5 per cent per annum and a scenario of 1.0 per cent per annum.

Interest Rate

The assumption of interest rate is the most important assumption, which is used for discounting the future cashflows to the present. The interest rate is assumed to be 8 per cent in the paper. Unlike the decrement rates, the assumption of interest rate does not impact the cohort profile, which

Chart 12: Attrition Shift –Impact on Pension Liability



Note: Case 1: Constant Attrition of 0.50 per cent
Case 2: Constant Attrition of 1.00 per cent
Source: Author's calculations.

solely depends upon various decrement rates alone. The paper computes the stochastic duration[16] of the pension liability. The definition of stochastic duration is similar to traditional duration, wherein the present value (PV) is replaced by APV. Accordingly, it is defined for pension liability as:

Modified Duration = % change in the APV of pension liability / one per cent change in the interest rate.

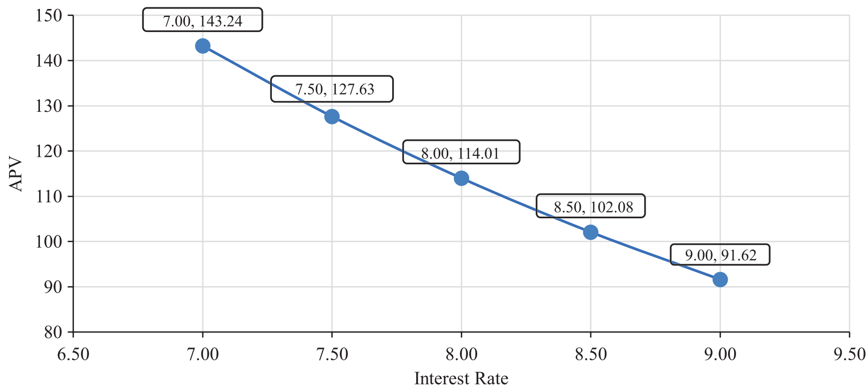
The modified duration is derived by computing the APV of pension liability at 7.50 and 8.50 per cent interest rates, as the pension liability is expected to have a non-zero convexity.[17] The variation in APV with respect to interest rate is given in Chart 13. The Chart shows inverse relationship between the two, as also seen in the case of traditional duration.

The modified duration is computed as 22.41. This means that the APV changes (decreases/increases) by 22.41 per cent due to a change (increase/decrease) of one per cent point (100 basis points) in the interest rate. From the chart, we see that the APV rises by 11.95 per cent on account of 50 basis

16 Stochastic duration is different and more complex from the traditional duration of fixed income, wherein cashflows are certain with regard to their timings and amount. Stochastic duration is based on uncertain cashflows, which depends on some contingent events.

17 The non-zero convexity results when the duration is not a constant and itself changes with the level of interest rates. The convexity is the derivative of duration of pension liability with respect to interest rate. The convex (positive) nature of convexity can be depicted from Chart 13, which is usual in long-term bonds also.

Chart 13: Interest Rate Shift - Impact on Pension Liability



Source: Author's calculations.

points fall in interest rate, but dips by 10.46 per cent when interest rate rises by 50 basis points. Accordingly, the pension liability has a positive convexity, which is common in any DB plan.

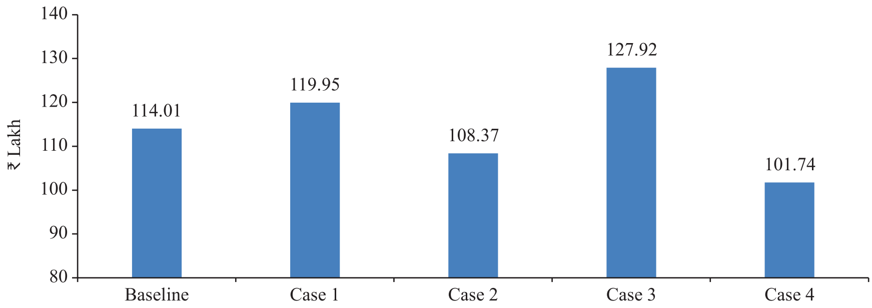
Salary Growth Rate and Inflation Rate

The assumption of salary growth rate is yet another important factor in assessing the pension liabilities. For the pension liabilities, the CAGR of 12.50 per cent is assumed. Now, an attempt is made to assess the impact on pension liabilities due to ± 100 basis points change in the CAGR. Thus, the impact on pension liabilities is seen in the two cases, namely where salary growth rate is 13.50 per cent and where it is 11.50 per cent. The assumptions of salary growth rates are applied only to the future years, *viz.,* 2022 onwards. This is because the computed salary scales till 2022 are based on factual data, which need not be modified.[18]

Further, the above salary growth rate assumption is applicable only to the active service members. As discussed earlier, the salary growth rate of the inactive service members (pensioners) largely tracks the inflation rates in respective years. Accordingly, two more scenarios have been added, which are pertaining to the inactive lives. It is assumed that the CAGR of pension is 7

[18] This is unlike other assumptions, such as, various decrement rates, which are applied during entire period. However, there are not known to the researcher.

Chart 14: Salary Shift-Impact on Pension Liability



Note: Case 1: Active salary CAGR = 13.50 per cent with unchanged inactive salary CAGR
Case 2: Active salary CAGR = 11.50 per cent with unchanged inactive salary CAGR
Case 3: Active salary CAGR = 13.50 per cent with inactive salary CAGR = 7.50 per cent
Case 4: Active salary CAGR = 11.50 per cent with inactive salary CAGR = 6.50 per cent

Source: Author's calculations.

per cent in the study. Now, a variation of ± 50 basis points in this growth rate *i.e.,* 7.50 and 6.50 per cent per annum is considered to reflect an inflation rate change by close to 50 basis points either way.

The scenarios of salary growth rates in the pre- and post-retirement phases are provided in Chart 14. From the Chart, it is observed that the assumption of salary growth rate is equally important as that of the interest rate. However, unlike interest rate, the salary growth rate has a positive association with the APV of the pension liability. In other words, a rise in salary will lead to increase in the APV and *vice-versa.* The APV increases by 5.21 per cent due to 100 basis points increase in pre-retirement salary CAGR (Case 1) and goes up further by 12.20 per cent (combined) due to additional increase in the post-retirement salary CAGR by 50 basis points (Case 3).

Similarly, the APV decreases by 4.95 per cent (Case 2) and 10.76 per cent (Case 4) due to fall in 100 basis points in the pre-retirement salary CAGR with and without 50 basis points fall in post-retirement salary CAGR respectively.

The scenario analysis of key factors in the above paragraphs provides useful insights for assessing the impact of APV of the pension liability. The summary of findings is given in Table 9.

Table 9: Scenario Analysis for Pension Liability

Scenarios	Impact on APV
Decrement Rates	
Mortality	
Case 1: $q'_x = 1.10 * q_x$ for all x	5.03 per cent (downward)
Case 2: $q'_x = 0.90 * q_x$ for all x	**5.57 per cent (upward)**
Attrition / Retirement	
Case 1: Constant Attrition of 0.50 per cent (1 in 200)	**4.32 per cent (upward)**
Case 2: Constant Attrition of 1.00 per cent (1 in 100)	5.00 per cent (downward)
Other Rates	
Interest Rate	
Case 1: Increase by 50 bp (8.50 per cent)	10.46 per cent (downward)
Case 2: Increase by100 bp (9.00 per cent)	19.64 per cent (downward)
Case 3: Decrease by 50 bp (7.50 per cent)	**11.95 per cent (upward)**
Case 4: Decrease by 100 bp (7.00 per cent)	**25.64 per cent (upward)**
Salary / Inflation Rates	
Case 1: Active salary CAGR = 13.50 per cent with unchanged inactive salary CAGR	**5.21 per cent (upward)**
Case 2: Active salary CAGR = 11.50 per cent with unchanged inactive salary CAGR	4.95 per cent (downward)
Case 3: Active salary CAGR = 13.50 per cent with inactive salary CAGR = 7.50 per cent	**12.20 per cent (upward)**
Case 4: Active salary CAGR = 11.50 per cent with inactive salary CAGR = 6.50 per cent	10.76 per cent (downward)

Source: Author's calculations.

The decrement rates impact the cohort profile, which in turn, impact the APV. The other factors (interest rate, inflation rate and salary escalation rate) do not have any impact on the cohort profile but rather impact the APV directly. The adverse impact is shown in bold in the Table.

V.6 Sensitivity of Assumptions – Worst Scenarios

The impacts, as shown in Table 9, are the marginal impacts, allowing one rate to vary at a time on a *ceteris paribus* basis. It is very important to consider the joint impacts by allowing all the rates to shift adversely at a time. Some of the rates are positively associated with APV, while others are

Table 10: Stress Test for Pension Liabilities

Key Factors	Level	Shocks
Mortality	Moderate Severe	$q'_x = 0.90 * q_x$ for all x $q'_x = 0.80 * q_x$ for all x
Attrition / Retirement	Moderate Severe	Constant Attrition of 0.50 per cent (1 in 200) Constant Attrition of 0.10 per cent (1 in 1000)
Interest Rate	Moderate Severe	Decrease by 50 bp (7.50 per cent) Decrease by 100 bp (7.00 per cent)
Salary CAGR	Moderate Severe	Active salary CAGR = 13.50 per cent with unchanged inactive salary CAGR Active salary CAGR = 13.50 per cent with inactive salary CAGR = 7.50 per cent

Source: Author's calculations.

associated negatively. Two worst scenarios *viz.,* moderate and severe scenarios are considered.

An attempt is made in this section to assess the impact on APV under two stress tests. The relevant rates are allowed to move in adverse directions with two levels (moderate and severe) as shown in Table 10. The adverse marginal impact is assessed. Accordingly, the adverse deviations of assumptions are applied jointly to assess impact of these shocks on liability and covered under the "Stress Tests".

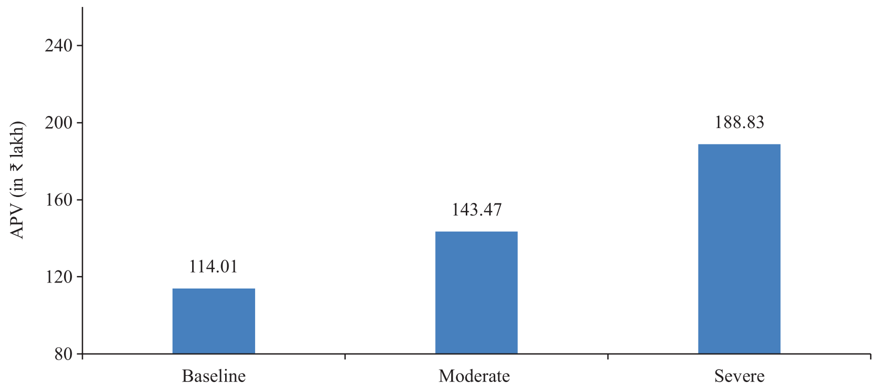
Two stress tests are applied as below:

- Test 1 - Moderate levels of all factors
- Test 2 – Severe levels of all factors

The impact on APV is exhibited in Chart 15. The APV rises significantly even in the moderate case, which shows the influence of joint impact of many moderate adverse movements occurring together. The APV rises by 25.84 per cent. The severe impact with profound levels of movements in key factors leads to a remarkable 65.63 per cent rise in the APV. The steep rise in the APV under this set of conditions reflects the vulnerability associated with a long-term liability of this kind.

The severe adverse movements of key rates are realistic, although rare. Hence, the possibility of even worse scenarios cannot be ruled out entirely. This is the reason why interest rate and salary CAGR are altered only by about

Chart 15: Stress Test – Impact on Pension Liability



Source: Author's calculations.

50-100 basis points. However, actual movements could be even more than this. And yet, a simultaneous adverse movement of all variables may be a rare situation.

The wage revision effective from November 01, 2007, which took place in 2010, may be a good example for illustration. While the wage revision turned out to be higher (17.5 per cent hike) than expected, the upward revision in the gratuity amount (from ₹3.5 lakh to ₹10 lakh), and also the offer of a second option for pension to existing employees and retirees coincided with the wage revision, resulting in huge amount of additional provisioning. This issue was also highlighted by RBI (2011) indicating the systemic concerns arising from this contingent liability.

Section VI
Conclusions and Way Forward

An attempt is made in this paper to construct and project salary indices for the Indian banking sector. The constructed indices fairly represent the Indian banking sector, covering major banks. Accordingly, the indices can be used as an important parameter for macroeconomic analysis. They can also be used as benchmark indices for many other institutions (including non-banking entities like insurance firms and PSUs). Apart from these, the findings may be useful for the financial regulators as well as to the actuarial community, especially for those involved in the pension and retirement benefit plans.

The study finds that the cost of the pension liability to banks under the DB plan could be 3 to 5 times higher than the DC plan, under certain set of assumptions. However, the overall burden of this liability may reduce gradually with the waning of employees in the DB plan and simultaneous increase in the number of employees with the DC plan.

The study also finds that the valuation of the pension liability is very sensitive to the assumption of the interest rate (used for discounting future payouts) and the assumption of future salary escalations. The impact of the interest rate changes on the cost of DB plans could be offset to a large extent by making liability driven investments (LDIs) in order to create matching assets subject to its availability.

The findings from the paper are expected to be useful for various HR-related policy decisions, such as, review of employers' long-term liabilities, committed wage revisions, terms of promotion, optimisation of demographic profile of officers, *etc*. The organisations may use these indices and assess the impact of such liabilities on their balance sheet within the overall framework of enterprise risk management. The degree of sensitivity to various actuarial assumptions of the pension liability as quantified in the paper is useful in identifying and assessing the role of these assumptions, which might be crucial in the overall valuation exercise of such contingent liabilities of the organisation.

The paper also opens up wide possibilities for future studies on this subject. For example, probability distribution of APV of pension liabilities as an output to the various input variables can be carried out using a Monte Carlo Simulation method as an extension to this stress test. This could be facilitated by the availability of the actuarial computing software.

References

Dadlani, D. & Jain, K. (2022). Sensitising to Sensitivities, 5th TechTalk in Employee Benefits, Institute of Actuaries of India, June.

European Commission (2011). The 2012 Ageing Report: Underlying assumptions and projection methodologies, *European Economy*, No. 4.

Franzen, D. (2010). Managing investment risk in defined benefit pension funds, *OECD Working Papers on Insurance and Private Pensions*, No. 38.

Formulae and Tables for Examinations (2002). The Faculty and Institute of Actuaries, United Kingdom.

Gingrich, E. (2015). US Retirement Market and the Role of the Actuary. Paper presented at the 17th Global Conference of Actuaries (GCA), Mumbai, February.

IBA (2015). Dearness Allowance Time-series Quarterly Rates, Indian Banks' Association.

IMF (2004). Market Developments and Issues, *Global Financial Stability Report*, September.

IMF (2017). Getting the Policy Mix Right, *Global Financial Stability Report*, April.

Kumar, V. (2013). Understanding trends in salary escalation rates in private sector, Research Project, Institute of Actuaries of India, Mumbai.

Kumar, V. (2014). Research Projects – Takeaways, A Presentation at the 10th Seminar on Current Issues in Retirement Benefits (CILA), Institute of Actuaries of India, September.

Saha, M. (2013). "RBI wants all PSBs to have uniform pension provision". Business Standard: http://www.business-standard.com/article/finance/rbi-wants-all-psbs-to-have-uniform-pension-provision-111071400059_1.html

Pandit, D. K. (2014). Employees Benefits and Actuarial Advice. Paper presented at the 16th Global Conference of Actuaries (GCA), Mumbai, February.

Pandit, J. D. & Kandoi, K. (2021). Actuarial Valuation of Employee Benefit – Impact of Social Security Code and COVID-19, A Presentation at the Western India Regional Council (WIRC) of the Institute of Chartered Accountants of India (ICAI), April.

Patel, Urjit R. (1997). Aspects of Pension Fund Reform: Lessons for India, *Economic and Political Weekly*, September, pp-2395-2402.

Peethambaran A. P. (2014). A Model (Deterministic) for Leave Benefit Valuation, Paper presented at the 16th Global Conference of Actuaries (GCA), Mumbai, February.

Ramaswamy, S. (2012). The sustainability of pension schemes, *BIS Working Paper*, No. 368, Monetary and Economic Department, Bank for International Settlement, Basel.

RBI (2011). *Financial Stability Report*, Reserve Bank of India, June issue (Box.3.2).

Sriram, K. (2014). Developing Appropriate Investment Strategies for Funded Employee Benefit Plans – Need & Scope for Actuarial Involvement. Paper presented at the 16th Global Conference of Actuaries (GCA), Mumbai, February.

Sriram, K. & Patel, K (2020). Sustainable Retirement for All. Paper presented at the 21st Global Conference of Actuaries (GCA), Mumbai, February.

Annex

Table A1: Annuity Function during Eligible Early Retirement (Age 47 years) to NRA (Age 60 years) *(Contd.)*

x	l_x	q_x	p_x	APV at Retirement at age x													
				47	48	49	50	51	52	53	54	55	56	57	58	59	60
47	100000.00	0.003168	0.996832	0.9876													
48	99683.20	0.003536	0.996464	0.9750	0.9841												
49	99330.72	0.003958	0.996042	0.9621	0.9711	0.9802											
50	98937.57	0.004436	0.995564	0.9490	0.9579	0.9668	0.9759										
51	98498.68	0.004969	0.995031	0.9356	0.9443	0.9531	0.9620	0.9710									
52	98009.24	0.005550	0.994450	0.9217	0.9304	0.9391	0.9478	0.9567	0.9656								
53	97465.29	0.006174	0.993826	0.9076	0.9161	0.9246	0.9333	0.9420	0.9508	0.9597							
54	96863.54	0.006831	0.993169	0.8930	0.9014	0.9098	0.9183	0.9269	0.9355	0.9443	0.9531						
55	96201.87	0.007513	0.992487	0.8781	0.8863	0.8946	0.9030	0.9114	0.9199	0.9285	0.9372	0.9460					
56	95479.10	0.008212	0.991788	0.8628	0.8709	0.8790	0.8873	0.8955	0.9039	0.9124	0.9209	0.9295	0.9382				
57	94695.03	0.008925	0.991075	0.8472	0.8551	0.8631	0.8712	0.8793	0.8876	0.8958	0.9042	0.9127	0.9212	0.9298			
58	93849.87	0.009651	0.990349	0.8313	0.8390	0.8469	0.8548	0.8628	0.8708	0.8790	0.8872	0.8955	0.9039	0.9123	0.9208		
59	92944.13	0.010393	0.989607	0.8150	0.8226	0.8303	0.8381	0.8459	0.8538	0.8618	0.8699	0.8780	0.8862	0.8945	0.9028	0.9113	
60	91978.16	0.011162	0.988838	0.7985	0.8059	0.8134	0.8211	0.8287	0.8365	0.8443	0.8522	0.8601	0.8682	0.8763	0.8845	0.8928	0.9011
61	90951.50	0.011969	0.988031	0.7816	0.7889	0.7963	0.8037	0.8112	0.8188	0.8265	0.8342	0.8420	0.8498	0.8578	0.8658	0.8739	0.8821
62	89862.90	0.012831	0.987169	0.7644	0.7716	0.7788	0.7861	0.7934	0.8008	0.8083	0.8159	0.8235	0.8312	0.8389	0.8468	0.8547	0.8627
63	88709.87	0.013765	0.986235	0.7469	0.7539	0.7609	0.7681	0.7752	0.7825	0.7898	0.7972	0.8046	0.8121	0.8197	0.8274	0.8351	0.8429
64	87488.78	0.014792	0.985208	0.7291	0.7359	0.7427	0.7497	0.7567	0.7638	0.7709	0.7781	0.7854	0.7927	0.8001	0.8076	0.8152	0.8228
65	86194.64	0.015932	0.984068	0.7108	0.7174	0.7241	0.7309	0.7377	0.7446	0.7516	0.7586	0.7657	0.7729	0.7801	0.7874	0.7947	0.8022
66	84821.39	0.017206	0.982794	0.6921	0.6986	0.7051	0.7117	0.7183	0.7251	0.7318	0.7387	0.7456	0.7525	0.7596	0.7667	0.7738	0.7811
67	83361.95	0.018635	0.981365	0.6729	0.6792	0.6855	0.6920	0.6984	0.7050	0.7115	0.7182	0.7249	0.7317	0.7385	0.7454	0.7524	0.7594
68	81808.50	0.020240	0.979760	0.6532	0.6593	0.6655	0.6717	0.6780	0.6843	0.6907	0.6971	0.7037	0.7102	0.7169	0.7236	0.7303	0.7372

Table A1: Annuity Function during Eligible Early Retirement (Age 47 years) to NRA (Age 60 years) *(Contd.)*

x	l_x	q_x	p_x	APV at Retirement at age x													
				47	48	49	50	51	52	53	54	55	56	57	58	59	60
69	80152.70	0.022040	0.977960	0.6329	0.6388	0.6448	0.6508	0.6569	0.6630	0.6692	0.6755	0.6818	0.6881	0.6946	0.7011	0.7076	0.7142
70	78386.14	0.024058	0.975942	0.6119	0.6177	0.6234	0.6293	0.6351	0.6411	0.6471	0.6531	0.6592	0.6654	0.6716	0.6779	0.6842	0.6906
71	76500.32	0.026314	0.973686	0.5903	0.5958	0.6014	0.6070	0.6127	0.6184	0.6242	0.6300	0.6359	0.6419	0.6479	0.6539	0.6600	0.6662
72	74487.29	0.028832	0.971168	0.5680	0.5733	0.5787	0.5841	0.5895	0.5950	0.6006	0.6062	0.6119	0.6176	0.6234	0.6292	0.6351	0.6410
73	72339.67	0.031638	0.968362	0.5449	0.5500	0.5552	0.5603	0.5656	0.5709	0.5762	0.5816	0.5870	0.5925	0.5980	0.6036	0.6093	0.6150
74	70050.99	0.034757	0.965243	0.5211	0.5260	0.5309	0.5359	0.5409	0.5459	0.5510	0.5562	0.5614	0.5666	0.5719	0.5773	0.5827	0.5881
75	67616.23	0.038221	0.961779	0.4966	0.5012	0.5059	0.5106	0.5154	0.5202	0.5251	0.5300	0.5349	0.5399	0.5450	0.5501	0.5552	0.5604
76	65031.87	0.042061	0.957939	0.4713	0.4757	0.4801	0.4846	0.4891	0.4937	0.4983	0.5030	0.5077	0.5124	0.5172	0.5220	0.5269	0.5318
77	62296.56	0.046316	0.953684	0.4453	0.4494	0.4536	0.4579	0.4622	0.4665	0.4708	0.4752	0.4797	0.4842	0.4887	0.4933	0.4979	0.5025
78	59411.24	0.051024	0.948976	0.4186	0.4226	0.4265	0.4305	0.4345	0.4386	0.4427	0.4468	0.4510	0.4552	0.4595	0.4638	0.4681	0.4725
79	56379.84	0.056231	0.943769	0.3914	0.3951	0.3988	0.4025	0.4063	0.4101	0.4139	0.4178	0.4217	0.4256	0.4296	0.4336	0.4377	0.4418
80	53209.54	0.061985	0.938015	0.3638	0.3672	0.3706	0.3741	0.3776	0.3811	0.3847	0.3883	0.3919	0.3955	0.3992	0.4030	0.4067	0.4105
81	49911.35	0.068338	0.931662	0.3358	0.3389	0.3421	0.3453	0.3485	0.3518	0.3551	0.3584	0.3617	0.3651	0.3685	0.3720	0.3754	0.3789
82	46500.51	0.075350	0.924650	0.3076	0.3105	0.3134	0.3163	0.3193	0.3223	0.3253	0.3283	0.3314	0.3345	0.3376	0.3407	0.3439	0.3471
83	42996.69	0.083082	0.916918	0.2794	0.2821	0.2847	0.2873	0.2900	0.2927	0.2955	0.2982	0.3010	0.3038	0.3067	0.3095	0.3124	0.3154
84	39424.44	0.091601	0.908399	0.2515	0.2538	0.2562	0.2586	0.2610	0.2635	0.2659	0.2684	0.2709	0.2735	0.2760	0.2786	0.2812	0.2838
85	35813.12	0.100979	0.899021	0.2240	0.2261	0.2282	0.2303	0.2325	0.2347	0.2369	0.2391	0.2413	0.2436	0.2458	0.2481	0.2505	0.2528
86	32196.75	0.111291	0.888709	0.1972	0.1991	0.2009	0.2028	0.2047	0.2066	0.2086	0.2105	0.2125	0.2145	0.2165	0.2185	0.2205	0.2226
87	28613.54	0.122616	0.877384	0.1714	0.1730	0.1747	0.1763	0.1779	0.1796	0.1813	0.1830	0.1847	0.1864	0.1882	0.1899	0.1917	0.1935
88	25105.06	0.135037	0.864963	0.1469	0.1483	0.1497	0.1511	0.1525	0.1539	0.1554	0.1568	0.1583	0.1597	0.1612	0.1627	0.1643	0.1658
89	21714.95	0.148639	0.851361	0.1239	0.1251	0.1263	0.1274	0.1286	0.1298	0.1310	0.1323	0.1335	0.1347	0.1360	0.1373	0.1386	0.1399
90	18487.26	0.163507	0.836493	0.1027	0.1037	0.1046	0.1056	0.1066	0.1076	0.1086	0.1096	0.1106	0.1117	0.1127	0.1138	0.1148	0.1159
91	15464.47	0.179726	0.820274	0.0835	0.0842	0.0850	0.0858	0.0866	0.0874	0.0883	0.0891	0.0899	0.0908	0.0916	0.0925	0.0933	0.0942
92	12685.10	0.197380	0.802620	0.0664	0.0670	0.0676	0.0682	0.0689	0.0695	0.0702	0.0708	0.0715	0.0722	0.0728	0.0735	0.0742	0.0749

Table A1: Annuity Function during Eligible Early Retirement (Age 47 years) to NRA (Age 60 years) *(Concld.)*

x	l_x	q_x	p_x	APV at Retirement at age x													
				47	48	49	50	51	52	53	54	55	56	57	58	59	60
93	10181.31	0.216547	0.783453	0.0515	0.0520	0.0525	0.0530	0.0535	0.0540	0.0545	0.0550	0.0555	0.0560	0.0565	0.0571	0.0576	0.0581
94	7976.58	0.237302	0.762698	0.0389	0.0393	0.0397	0.0400	0.0404	0.0408	0.0412	0.0415	0.0419	0.0423	0.0427	0.0431	0.0435	0.0439
95	6083.72	0.259706	0.740294	0.0286	0.0288	0.0291	0.0294	0.0296	0.0299	0.0302	0.0305	0.0308	0.0310	0.0313	0.0316	0.0319	0.0322
96	4503.74	0.283813	0.716187	0.0203	0.0204	0.0206	0.0208	0.0210	0.0212	0.0214	0.0216	0.0218	0.0220	0.0222	0.0224	0.0227	0.0229
97	3225.52	0.309659	0.690341	0.0139	0.0140	0.0141	0.0142	0.0144	0.0145	0.0147	0.0148	0.0149	0.0151	0.0152	0.0153	0.0155	0.0156
98	2226.71	0.337265	0.662735	0.0091	0.0092	0.0093	0.0094	0.0094	0.0095	0.0096	0.0097	0.0098	0.0099	0.0100	0.0101	0.0102	0.0103
99	1475.72	0.366630	0.633370	0.0057	0.0058	0.0058	0.0059	0.0059	0.0060	0.0060	0.0061	0.0061	0.0062	0.0063	0.0063	0.0064	0.0064
100	934.68	0.397733	0.602267	0.0034	0.0034	0.0035	0.0035	0.0035	0.0036	0.0036	0.0036	0.0037	0.0037	0.0037	0.0038	0.0038	0.0038
101	562.92	0.430529	0.569471	0.0019	0.0019	0.0020	0.0020	0.0020	0.0020	0.0020	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0022
102	320.57	0.464950	0.535050	0.0010	0.0010	0.0010	0.0010	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
103	171.52	0.500904	0.499096	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0006	0.0006	0.0006	0.0006
104	85.61	0.538278	0.461722	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003
105	39.53	0.576942	0.423058	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
106	16.72	0.616752	0.383248	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
107	6.41	0.657553	0.342447	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
108	2.19	0.699191	0.300809	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
109	0.66	0.741515	0.258485	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
110	0.17	0.784383	0.215617	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
111	0.04	0.827673	0.172327	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
112	0.01	0.871285	0.128715	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
113	0.00	0.915145	0.084855	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
114	0.00	0.959214	0.040786	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
115	0.00	1.000000	0.000000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Annuity (In Arrears)				**26.8372**	**26.0911**	**25.3417**	**24.5891**	**23.8340**	**23.0766**	**22.3176**	**21.5576**	**20.7970**	**20.0366**	**19.2769**	**18.5186**	**17.7622**	**17.0084**

Reserve Bank of India Occasional Papers
Vol. 43, No. 1: 2022

Do Bank Mergers Improve Efficiency? The Indian Experience

Snehal S. Herwadkar, Shubham Gupta and Vaishnavi Chavan*

Received on: June 17, 2022
Accepted on: December 07, 2022

In recent years, the Indian banking sector has witnessed hectic activity in the merger space. Compiling data on bank mergers since 1997, the paper analyses the impact of bank mergers on the short-term and medium-term performance of the acquirer banks. Data envelopment analysis (DEA) suggests that the efficiency of acquirers improved post-merger due to an increase in scale or productive capacity. Financial ratio analysis, which compares the pre- and post-merger performance of acquirers, reinforces the findings of efficiency analysis. These results are robust even after controlling for industry-wide impact. The event study analysis employed for bank mergers between 2019 – 2020 indicates an increase in shareholders' wealth of the acquiree banks. The study identifies geographical diversification and greater focus on interest earnings as a source of income as the key factors behind post-merger improvement in bank efficiency.

JEL Classification: C61, G21, G34

Keywords: Bank mergers, M&As, efficiency, financial ratios, DEA, Tobit model, event study

---

* Snehal S. Herwadkar is Director, Shubham Gupta was Manager and Vaishnavi Chavan was Research Intern in the Department of Economic and Policy Research, Reserve Bank of India, Mumbai. The authors are thankful to the reviewers and participants of the DEPR Study Circle seminar for their insightful comments and suggestions. We are also grateful to an anonymous external referee for constructive and valuable suggestions for improving the paper's content. We thank the editorial team of Development Research Group, DEPR, for their constant support. The views expressed in the paper are of the authors and do not necessarily reflect the views of the Reserve Bank of India. The authors take responsibility for errors, if any, that may have remained.

Introduction

In the recent years, the Indian banking sector has witnessed a flurry of activity in the merger space. In one of the biggest consolidations of the sector, ten public sector banks (PSBs) were merged into four, effective April 1, 2020. The Government of India while announcing the merger plan suggested that, "The adoption of best practices across amalgamating entities would enable the banks improve their cost efficiency and risk management…" (PIB, 2019). More than two years have elapsed since the mega-merger and the impact assessment in the literature appears to be divided. While certain studies suggest that non-performing assets (NPAs) of weak merging banks declined by 10 per cent, almost entirely due to a decline in strategic defaults (Kashyap *et al.*, 2022), some researchers, on the other hand, argue that, "the merger decisions were not necessarily on efficiency grounds, and hence, post-merger benefits are minimal" (Das and Kumbhakar, 2022). The aim of the present paper is to analytically evaluate the impact of mergers on the acquirer banks.

The expected benefits of mergers and acquisitions (M&As) in financial institutions worldwide, including in India, are cost reduction, profit maximisation, and gains through portfolio or geographical diversification. Mergers impact shareholders' wealth, alter capital infusion requirements in case of weak banks, and can also lead to reduced competition and creation of too-big-to-fail (TBTF) banks that may have a systemic impact. Historically, M&As in banks are aimed at improving financial performance and efficiency, either by resolving the problem of distressed banks or by ameliorating economies of scale.[1] For example, most of the European bank mergers in the 1990s were either for defensive purpose of inefficient acquired entity or for improving their competitiveness in the European Union (Azofra *et al.*, 2008). Evidence from the US banks suggests that mergers strengthened the credit market by allowing banks to achieve higher economies of scale while minimising their costs (Al-Sharkas, 2008). In the emerging market economies (EMEs) as well, bank mergers were undertaken primarily for revenue maximisation and

---

1 Mergers between corporates are usually aimed at creating value through revenue synergies or cost synergies, diversification benefits by entering different lines of business, acquisition of assets of the target company, increase in firms' capacity, and tax benefits. As such, mergers in the banking or financial sector can be treated as special cases of corporate mergers.

cost reduction (Berger *et al.*, 1998). Higher scale efficiency is documented to be one of the major causes behind mergers of South African banks post global financial crisis (Wanke, 2017). Protecting distressed banks was a key motivation behind EME bank mergers, especially those led by government policy (Sufian, 2007; Joshua, 2011). However, economic literature so far is not unanimous on "….whether the participating banks indeed benefit from M&As, whether their customers share the benefits, or whether systemic risks increase or decrease after the merger…" (DeYoung *et al.*, 2009).

Globally, previous studies have employed performance ratio approach, efficiency analysis and event studies to evaluate the benefits of bank M&As. Contemplating bank mergers since 1997, for both public and private sector banks, the current study employs all the three approaches used in the literature to gauge whether bank mergers in India resulted in short-term and medium-term gains for the acquirer banks. The paper also attempts a deep dive into factors contributing to efficiency gains. In particular, the paper seeks to answer four questions: a) What were the efficiency characteristics of acquirer and acquiree banks pre-merger? In particular, whether the mergers were amongst equals or between a strong and a weak bank?; b) Whether the financial performance and efficiency of acquirers improved or deteriorated post-merger? And what contributed to the efficiency gains post-merger—gains in managerial prowess or scale efficiencies?; c) Did geographical diversification or changes in the source of income (greater focus on interest earnings as compared to non-interest earnings) had a role to play in efficiency improvement?; and d) How did the recent mergers perform, especially with reference to their impact on shareholders' wealth.

Our findings, using the non-parametric technique of data envelopment analysis (DEA) suggest that mergers, on an average, improved the efficiency of acquirers—both in the short-term (1 year and 3 years since merger) and medium-term (5 years since merger). A more nuanced analysis suggests that this improvement was due to increased scale of productive capacity (scale efficiency). These findings are supported by financial ratio approach, where the pre-merger financial performance of acquirers is compared to that in the post-merger period. Additionally, the results remain robust when compared to the average performance of the 'control group'—consisting of all scheduled commercial banks (SCBs). The event study approach employed for mergers during 2019-2020, where adequate data is still not available, suggests that mergers resulted in an increase in shareholders' wealth of the acquiree banks, while the share price of acquirer banks witnessed a temporary blip. Furthermore, the paper makes an innovative contribution to the existing literature by analysing factors that may have contributed to efficiency gains. Using Herfindahl-Hirschman index (HHI) as a measure of geographical concentration, the paper finds that mergers have led to higher geographical diversification for acquirers. Results of panel Tobit regression analysis suggest that geographical diversification coupled with changes in earning sources—away from non-interest income to interest income—resulted in post-merger improvement in bank efficiency.

The rest of the paper is structured as follows: Section II reviews the relevant literature. Section III presents an overview of bank M&As in the Indian context. Section IV gives a detailed description of the data and methodology used. Section V is devoted to empirical findings and analysis of results. Section VI concludes the study.

Section II
Literature Review

The literature on bank M&As is vast and can be largely divided into four strands. Studies that focus on the impact of M&As on the financial performance of banks employ the performance analysis using accounting ratios, efficiency frontier analysis using either DEA or stochastic frontier analysis (SFA), and/or event study analysis (Kolaric and Schiereck, 2014). Another strand of literature focuses on the non-financial motives behind mergers. These include 'fringe utilities' like enhanced managerial power of the CEO and the financial benefits of becoming a 'too-big-to-fail (TBTF)' institution. Studies have also evaluated the benefits accrued due to various types of diversification—across financial products and across geographies—as a fallout of mergers. Lastly, some studies are devoted to documenting the benefits received by borrowers, depositors, and external stakeholders due to mergers.

The event study is another commonly used technique of impact assessment for banking M&As. This method involves investigating the publicly traded stock returns of the acquirer and acquiree banks around the merger announcement date. Specifically, abnormal/expected stock returns are estimated, and a merger is considered successful if the actual stock returns received by the investors exceed the abnormal returns. In the bank M&As literature, most event study analysis suggest a positive and statistically significant abnormal stock returns for the acquiree banks and negative returns for the acquirers (Hannan and Wolken, 1989; Cornett and Tehranian, 1992; Houston and Ryngaert, 1997; DeLong, 2003a; Campa and Hernando, 2006; Al-Sharkas and Hassan, 2010). However, recent studies for the US, Euro and EMEs report non-negative returns for the acquirers also (Kolaric and Schiereck, 2014). Kiymaz (2004, 2013) reports that the US banks involved in cross-border M&A transactions generated positive abnormal returns for the acquirer and acquiree banks. Kolaric and Schiereck (2013) and Goddard *et al.* (2012) find positive abnormal stock returns for Asian and Latin American bank mergers over a long-term period. Similarly, Ismail and Davidson (2005, 2007) report positive abnormal stock returns for both the parties involved in the merger transaction for European banks. As per Houston *et al.* (2001), better valuation of bank M&A transactions or better access to information for the acquirers may have attributed to positive abnormal returns for the acquirer banks.

Similar to the results from developed economies, evidence from EMEs showed mixed or no significant impact of mergers on cumulative abnormal returns (CARs)[2] to the shareholders of acquirer banks. Evidence from the Middle East and North African region showed that mergers did not have significant positive or negative impact on shareholders' wealth (Sindi *et al.*, 2018). The study on Indian banking mergers found a mixed impact of the announcement of bank mergers—merger announcements had limited impact on the volatility of share prices and no significant impact on the liquidity of the shares of acquirers (Kumar *et al.*, 2013). Since the merger news is often leaked in the market much before the official announcement day, researchers

2 Detailed discussion on event study analysis, which uses calculations on cumulative abnormal returns is provided in the next section.

have also used ‘date of leakage’ *i.e.*, the date on which the news of the merger first reached the market instead of the official announcement date (Houston and Ryngaert, 1994, 1997; Houston *et al.,* 2001), while others have simply extended the event window to account for the information leakage (Amihud *et al.*, 2002).

In the case of performance studies using accounting ratios, pre- and post-merger financial health parameters like capital adequacy, profitability, operational efficiency, liquidity, asset quality, loan loss provisions, *etc.* are compared. A merger is considered successful if the combined entity’s financial performance improves post-merger. The empirical evidence from the studies using accounting ratios to ascertain the success/failure of bank M&As is heterogeneous. In the US, performance studies have obtained both positive (Boyd and Graham, 1988; Cornett *et al.*, 2006) and negative (Linder and Crane,1993; Knapp *et al.*, 2005) results from bank M&As. Similarly, results from performance studies for European banking M&As are also mixed and highly sensitive to the period under investigation (Kondova and Burghof, 2007). Reda (2013) showed that profitability and liquidity ratios for Egyptian banks deteriorated post-merger, however, there was a significant improvement in their risk management practices. In the Indian context, Bishnoi and Devi (2015) did not find any significant improvement in performance indicators of acquirer banks post-merger.

A few studies also use a control/peer group to account for the noise not directly related to merger-related sources. Kwan and Wilcox (1999) show that for the US bank mergers between 1985 and 1997, the operating expenses (both labour cost and occupancy expense) of the merged entities reduced significantly compared to their non-merging peers. Other studies simply exclude the merger year to account for the distortion in cost performance due to differing accounting methods (Linder and Crane, 1993; Cornett *et al.*, 2006).

Efficiency analysis for bank M&As, on the other hand, employs frontier analysis using accounting data to estimate a cost or profit function of the best performing bank in the sample, to which other banks are compared. The closer a bank gets to the efficiency frontier after the merger, the higher is the improvement in its efficiency. Parametric techniques like the SFA and non-parametric techniques like DEA are used to estimate efficiency (Liu and Tripe, 2003). However, non-parametric techniques are preferred as they avoid the complexities arising out of assuming a specific functional form *i.e.,* distributional assumptions about the explained/error terms, restriction for minimum sample size, *etc.*

Worldwide evidence on whether bank mergers lead to efficiency gains is mixed, both in the developed and EMEs. In a study of 57 US bank mergers between 1981–1989, Akhavein *et al.* (1997) found that mergers led to improvement in profit efficiency of the acquiring banks. Similar results were observed for the UK bank mergers between 1981–1993 (Haynes and Thompson, 1999). Al-Sharkas *et al.* (2008) show that the US bank mergers between 1985–1999 improved both cost and profit efficiency of the acquirer banks. On the other hand, Fixler and Zieschang (1993) reported deterioration in cost efficiency of the US banks that underwent M&As in 1986. Overall, a majority of efficiency studies on the US bank mergers report mixed results (Rhoades, 1998; DeYoung, 1997; Fried *et al.*, 1999; Peristiani, 1997).

Comparing pre- and post-merger DEA efficiency scores of Australian trading banks, Avkiran (1999) concluded that before merger, acquirer banks were more efficient than their acquirees and in-market mergers resulted in increased efficiency post-merger. Similarly, evidence for bank mergers between 1989-1998 in New Zealand suggested improvement in employee productivity and post-merger efficiency gains in five out of six banks (Liu and Tripe, 2003). Echoing these findings for Egypt, Reda (2013) documented significant improvement in managerial efficiency of banks post-merger. In a study of seven bank mergers in Malaysia during 2000, Sufian (2007) suggested that the technical efficiency of the acquirer banks improved post-merger. Sufian and Majid (2009) also show that Singaporean banks became relatively more scale inefficient after mergers. In Taiwanese banking sector, scale efficiency of acquirers improved post-merger due to portfolio diversification and therefore, Lee *et al.* (2013) suggested multi-product strategy to lower production costs.

In the Indian banking sector, evidence proposed by Jayaraman *et al.* (2014) suggests that the technical efficiency of merged banks deteriorated in immediate periods post-merger but improved in the third year since merger. However, mergers did not have significant impact on profitability and cost efficiency. In contrast, the findings of Singh (2009) suggested that bank mergers post-2000 did not have any adverse impact on profit and cost efficiency of acquiring banks and short-term losses were recovered quickly. Das and Kumbhakar (2022) suggested that the recent wave of mergers in India had only limited efficiency gains. Niche segment of regional rural banks (RRBs) were also documented to achieve remarkable improvement in post-merger technical efficiency, pure technical efficiency as well as scale efficiency (Antil *et al*., 2020). Nishat (2020) found that although scale efficiency of Indian PSBs did not change significantly post-merger, their managerial efficiency improved significantly due to better planning and managing techniques.

Overall, the empirical evidence of impact of bank M&As has been mixed across all the three prominent methodologies. Each methodology has its own distinctive pros and cons while assessing a merger transaction. Event study analysis is best suited when the ultimate goal of the analysis is to focus on shareholders' wealth creation. However, the market assessment of the merger deal may be erroneous around the merger announcement date which makes interpreting short-term success as an indication of long-term success questionable (Kolaric and Schiereck, 2013). Efficiency and performance studies, on the other hand, are more useful to investigate the medium to long-term effects of M&As.

Section III
M&As in the Indian Banking Industry

Analogous to other EMEs, bank mergers in India were government policy driven during the nationalisation phase (1960 to 1969), when distressed banks were consolidated with stronger banks. Subsequently, however, there was a relative lull in the merger activity till the economy embarked on the liberalisation process (Table 1). The intellectual rationale for bank mergers in the post-liberalisation period was provided by the Narasimhan Committee Reports (1991, 1998)—that recommended banking consolidation, both in the public and private sectors and even with financial institutions and NBFCs—to make them stronger and more competitive.

Table 1: Bank M&As in India

Period	**Number of Mergers**
Pre-nationalisation of banks (1961-1968)	46
Nationalisation to Liberalisation period (1969-1996)	14
Post-Liberalisation period (1997-2022)	40
Total	**100**

Sources: RBI, 2008; and STRBI, various issues.

In contrast to the nationalisation phase, the consolidation during the post-liberalisation phase was primarily market-driven with an objective to enhance efficiency and gain greater resilience. During 1997-2022, there were 40 bank amalgamations, out of which 12 were between private sector banks (PVBs) and PSBs, 16 were amongst PSBs and the remaining 12 were between PVBs and foreign banks. The consolidation of State Bank of India (SBI) with its associates (during 2008-2017) and the mega merger of ten banks into four in April 2020 account for majority of PSB mergers. Further, bank amalgamations prior to 1999 were primarily triggered by weak financial conditions of the acquiree banks whereas post-1999, business and commercial considerations (such as, the need for increasing market share, operational synergies, acquisition of a business unit or segment, *etc.*) have also influenced mergers between healthy banks (Leeladhar, 2008).

Section IV
Data and Methodology

The study covers all registered M&As in the Indian commercial banking industry between 1997 to 2020. The following criteria was used for a merger to be considered under the study: (a) consistent data availability in line with the research design; (b) both the acquirer and the acquiree bank should either belong to public sector (PSB) or private sector (PVB) bank-group[3], and (c) a single merger application within the period of analysis, although there could be multiple acquiree banks during the same merger year. In cases with multiple mergers in consecutive years, the latest merger application was

[3] Since M&As involving other bank groups, such as foreign banks, constituted a minuscule share of the sample, they were not considered.

considered[4], and a single merger observation was considered for cases where multiple acquiree banks were merged with an acquirer in the same year.[5] After applying these criteria, the sample reduced to 17 merger cases during 1997-2017 (Annex I) and five merger cases during 2019-2020 (Annex II). Table 2 illustrates the descriptive statistics of the acquiree and acquirer banks involved in M&As during 1997-2017.

Bank-level financial data from 1994 to 2022 was compiled from audited financial statements of banks and Statistical Tables Relating to Banks in India (STRBI) published by the Reserve Bank of India (RBI). Apart from acquiree and acquirer banks, data was also collated for all the remaining PVBs and PSBs operating in India, as the latter group formed the 'control group' for statistical analysis.

Table 2: Data Description[6]

(₹ crore)

Bank Type	Summary Statistics	Net Loans & Advances	Invest-ments	Total Assets	Deposits	Capital Reserves & Surplus	Operating Profit
Acquiree Banks	Average	28,881	11,256	45,667	34,320	7,137	754
	SD	93,410	33,338	142,963	105,210	26,007	2,526
	Median	1,665	1,713	4,444	3,631	244	46
	Min	15	10	43	36	5	(273)
	Max	389,474	139,578	597,138	440,227	107,847	10,479
Acquirer Banks	Average	176,982	80,606	300,490	218,677	20,501	5,575
	SD	362,127	145,635	587,441	434,379	36,441	10,834
	Median	34,756	25,055	72,915	53,986	3,381	1,347
	Min	2,110	2,861	6,982	6,073	308	82
	Max	1,463,700	575,652	2,357,618	1,730,722	144,274	43,258

Note: Data pertains to end-March of the year prior to the M&A year.
Source: STRBI, Authors' calculations.

4 For example, Centurion Bank Ltd. acquired Bank of Punjab in 2005 and the new entity was called Centurion Bank of Punjab Ltd. It further acquired Lord Krishna Bank in 2007 and then ultimately got merged with HDFC bank in 2008. In our sample, only the merger between HDFC bank and Centurion Bank of Punjab Ltd. was considered.

5 The merger of five associate banks and Bhartiya Mahila Bank with the State Bank of India was considered a single observation.

6 The high standard deviation is mainly due to inclusion of SBI and its associates, which is much larger in size as compared to others in the sample.

To measure the impact of merger, comparing data of up to three years prior to the merger event with that up to three years afterwards is the most common practice in the literature (Rhoades, 1998; Avkiran, 2006; Liu and Tripe, 2003; Sufian and Majid, 2009; Bishnoi and Devi, 2015). Most researchers have argued that the performance of banks might deteriorate in the immediate years following merger due to organisational changes, but a minimum of three-year window is required to absorb the effects and to reflect its impact on managerial and scale efficiency (DeYoung *et al.,* 2009; Berger *et al.*, 1998). On the other hand, any time window beyond 5 years will be too long, where apart from factors relating to mergers, influence of other factors may dominate. Motivated by earlier literature, the study analyses the impact of M&As on the financial performance and efficiency of the merged entities in short term *i.e.,* (-1, +1) years, (-3, +3) years and the medium-term (-3, +5) years.

A. Financial Ratio Analysis

Financial ratios are the health indicators of banking institutions. The current study computes mean financial ratios of the banks involved in M&As over three years before merger to see if the acquirers had better financial health than their acquirees. The study also compares the mean financial ratios of the acquirers over the short-term — (-1, +1), (-3, +3) and the medium-term (-3, +5) event window, excluding the merger year to see if the financial conditions of the acquirers improved post-merger. Following Reda (2013) and Cornett *et al.* (1992), the study looks at 15 financial ratios, covering liquidity, profitability, operating efficiency, capital adequacy, asset quality and NPA provisions aspects that have implications for revenue enhancement, cost cutting and solvency of the banks. Detailed definitions for each are provided in Annex III.

Although financial ratio analysis is the most rudimentary and widely used approach to investigate the effects of banking M&As, it has certain limitations. One of the major drawbacks is that it relates only one input to one output at a time (Chen and Ali, 2002). Banks typically use multiple inputs to produce one or more outputs, with no one-to-one correspondence. A performance metric based on the ratio of a single output to a single input fall short of capturing the comprehensive view of their performance. To avoid this, literature suggests that the ratio analysis may be complemented with other approaches, such as the frontier approach (Thanassoulis *et al.,* 1996). In this vein, the present study also explores the non-parametric DEA frontier approach to analyse the impact of banking M&As in the Indian context.

B. Data Envelopment Analysis

In the recent years, researchers have increasingly used efficiency measures—such as DEA and SFA to gauge the impact of M&As. SFA requires a parametric specification for the efficient frontier and its statistical noise (Anwar, 2011). In contrast, the non-parametric approaches such as DEA—developed by Charnes, Cooper and Rhodes (CCR) in 1978—avoids the complexities arising out of assuming a specific functional form (*i.e.,* distributional assumptions about the explained/error terms, restriction for minimum sample size, *etc.*). Moreover, for banking services, DEA is a more suitable approach as it helps in simultaneously modelling multiple outputs for a given set of inputs and allows researchers to choose a combination of inputs and outputs, regardless of different measurement units (Avkiran, 2006).

DEA uses linear programing methods to construct a 'grand frontier' based on a piecewise linear connection of the best-practice decision making units' (DMUs) efficiency scores, to which other DMUs in the sample are compared, to obtain relative efficiency scores. In essence, it estimates relative efficiency scores by maximising the ratio of weighted outputs to weighted inputs and a DMU is said to have become efficient if it moves closer to the grand frontier (refer to Annex IV for details). The relative efficiency of each DMU lies between 0-100, where an efficiency score of 100 implies that the DMU is situated at the best-practice frontier. On the other hand, an efficiency score of less than 100 implies that the DMU is relatively inefficient than the best-practice DMU and imply sub-optimal behaviour. Thus, the advantage of using DEA approach is that it also highlights the areas that need improvement for each DMU (Sufian and Majid, 2009).

DEA model developed by CCR in 1978 estimates the overall technical efficiency (TE) scores of input-output transformations under the assumption of constant returns to scale (CRS). Later, in 1984, Bankers, Charnes and

Cooper (BCC) extended the CCR model to include variable returns to scale (VRS) which provides estimates for pure technical efficiency (PTE) devoid of scale effects. The scale efficiency (SE) is computed as the ratio of technical efficiency to pure technical efficiency, *i.e.*, $SE = TE/PTE$

This paper employs the output-oriented[7] DEA with CRS to compute TE of acquiree and acquirer banks involved in M&As and then decomposes the TE into two mutually exhaustive components – PTE and SE to identify the sources of efficiency (inefficiency) post-merger. In essence, PTE measures the controllable, managerial or overall organisational efficiency in transforming a DMU's inputs into outputs whereas SE captures the efficiency of a DMU attributable to its size and production level. A scale efficient firm will produce where production frontier exhibits CRS (Alexander and Jaforullah, 2005; Sufian, 2007; Reda, 2013).

Choice of Production Approach

The choice of appropriate inputs and outputs for measuring banking efficiency remains a contentious issue among researchers. As majority of banking services are jointly produced where the costs/revenues are jointly assigned to a bundle of financial products, it is difficult to classify inputs and outputs separately (Antil *et al*., 2020). Nevertheless, two main approaches to model bank production dominate the literature: production approach and intermediation approach (Sealey and Lindley, 1977).

Under the production approach—pioneered by Benston (1965)—output is measured as the number of accounts rather than the rupee value of services provided and costs include all operating expenses, except the interest paid on deposits (as deposits are considered as output). This approach focuses on the operational aspect of banking business and is more appropriate for measuring branch-level efficiency (Berger and Humphrey, 1997).

The intermediation approach (also known as the asset approach), on the other hand, considers banks as financial intermediaries between savers and borrowers that purchase labour, physical capital (fixed assets and equipment), deposits and other liabilities to produce interest-earning assets such as loans and

---

7 In the case of output-oriented DEA models, the merged entity is said to become more efficient post-merger if its output increases more than proportionately to the increase in its inputs.

advances, investments and other securities (Sealey and Lindley, 1977). Unlike the production approach, outputs are measured as the rupee value of assets and this approach is well suited for bank-level efficiency studies. Moreover, this approach includes interest expense (which constitute a large proportion of a bank's total cost) along with operational expenses (Mester, 1987). Following several previous studies (Charnes *et al*., 1990; Bhattacharyya *et al*., 1997; Avkiran, 2006; Sathye, 2001; Isik, 2002; Liu and Tripe, 2003; Sufian and Majid, 2009), the current paper also uses the intermediation approach for measuring banking efficiency.

Choice of Inputs and Outputs for Bank Production

In DEA, a limited number of variables are employed to avoid the issue of over-specification of the model. Moreover, using a large number of variables may inflate the efficiency scores and in case of very small samples, this may lead to all DMUs being on the efficient frontier. On the other hand, omission of relevant variables can lead to underestimation of efficiency with the effect being amplified in case of irrelevant variables in the DEA model. Thus, the current study uses a limited number of inputs and outputs which satisfy the rule of thumb specified by Cooper *et al*. (2002).[8]

Although the choice of inputs-outputs in a DEA model is left to the user's discretion, judgement, and expertise (Nataraja and Johnson, 2011), the selection of inputs and outputs in the current study is guided by the availability of data and previous studies. As per Avkiran (1999), potential inputs under the intermediation approach include deposits, interest expense, non-interest expense, number of employees (full time equivalent), other purchased capital, physical capital (fixed assets and equipment), demographics and competition. Potential outputs include net interest income, non-interest income, consumer loans, housing loans, commercial loans and investments. Given that DEA is sensitive to the choice of input-output mix, this study explores four DEA models (Table 3) such that the above-mentioned rule of thumb is satisfied for all four models.

---

[8] The Rule of thumb is specified as:

$n \geq max\,\{m * s, 3(m + s)\}$

where, n is the number of DMUs, m is the number of inputs, and s is the number of outputs.

Table 3: DEA Model Specification

	Model 1	Model 2	Model 3	Model 4
Inputs	1. Non-Interest Expense 2. Interest Expense	1. Non-Interest Expense 2. Interest Expense	1. Non-Interest Expense 2. Interest Expense	1. Non-Interest Expense 2. Deposits 3. Borrowings
Outputs	1. Non-Interest Income 2. Net-Interest Income	1. Investments 2. Total Loans	1. Non-Interest Income 2. Net-Interest Income 3. Total Loans 4. Investments	1. Operating Income 2. Total Loans 3. Investments

In line with the past research (Avkiran, 2006; Sathye, 2003; Kao and Lui, 2004; Sufian, 2007; Reda, 2013; Sonai *et al.*, 2020), interest and non-interest expense are used as the input variables in the first three models. These inputs are used to generate interest and non-interest income—the outputs in Model 1. Alternately, these inputs also help generate investments and total loans—the outputs in Model 2. Model 3 combines the input-output mix of the earlier two models and Model 4 uses a different set of input-output combination that account for a larger proportion of the intermediation function of banking business (Liu and Tripe, 2003). Here, deposits include domestic and foreign demand, savings and term deposits of customers and other banks and borrowings comprise of borrowings from the central bank (RBI), other banks and agencies. Since DEA efficiency scores change with the change in inputs and outputs, average efficiency scores across these four models are used as robust estimates of banking efficiency.

C. Tobit Regression

Given that the efficiency scores are bounded within [0,100], the study uses panel data Tobit model to investigate the factors that could have led to efficiency improvement for the acquirer post-merger. The Tobit regression for panel data with individual specific effects has the following specification:

$$y_{it} = \alpha + \beta x_{it} + \mu_i + \epsilon_{it}$$

$$f(x) = \begin{cases} a, & if\ y_{it} \leq a \\ y_{it}, & if\ a \leq y_{it} \leq b \\ b, & if\ y_{it} \geq b \end{cases}$$

where, a and b represent the lower and upper bound, respectively, $i = 1, 2, \ldots . n$ represent the i^{th} individual, $t = 1, 2, \ldots . T_i$ represent t^{th} time periods for the i^{th} individual, $\mu_i \sim N(0, \sigma_\mu^2), i.i.d$ represent the time-invariant individual specific effect and ϵ_{it} $(0, \sigma_\epsilon^2), i.i.d$ the remaining disturbance term, independent of μ_i . Unlike the uncensored linear panel data model, the fixed-effects panel Tobit model suffers from the incidental parameters problem (Neyman and Scott, 1948; Lancaster 2000), *i.e.,* the estimated coefficients are inconsistent unless the number of time periods T_i approaches infinity for each individual i. Since the time period considered under the study is relatively small (6 to 8 time periods), we prefer the random effects for the panel Tobit regression model.

D. Event Study

Following (MacKinlay, 1997; Mathur *et al.*, 2021), we employ an event study model to evaluate bank mergers during 2019-2020. Under this approach, the change in shareholders' wealth or abnormal return—the stock return in excess of the expected return is calculated using the market model as:

$$\hat{R}_{bt} = \hat{\alpha}_i + \hat{\beta}_i R_{Mt}$$

where, R_{bt} represented the daily stock market return for bank b at time t, R_{Mt} is the daily return for the Nifty-50 index.[9] The model is estimated over a period of $(T - 91{:}\, T - 11)$, T being the event date and then abnormal returns (ARs) for each bank b over a window of (-1, +1) days[10] are calculated as:

$$AR_{bt} = R_{bt} - \hat{R}_{bt} \;\forall\, T \in (-1, 0, +1)$$

The calculated ARs are indexed to 0 on day (-1) of the event window and cumulated over the next days to obtain the cumulative abnormal returns (CARs). The average CARs for all bank in the sample over each day of the event window are plotted, using bootstrap 95 per cent confidence intervals.

9 Nifty-50 index represent the benchmark stock market index of the 50 largest firms in India.

10 A tight window around the event date ensures robust accounting for anticipation effects and avoids any confounding factors that may influence the abnormal returns (Gurkaynak & Wright, 2013).

Section V
Empirical Results

The empirical analysis of the paper can be broadly divided into two parts. In the first part, using data on bank M&As during 1997-2017, we evaluate three questions: (a) were the acquirers more financially sound and efficient than their acquirees before the merger *i.e.,* over (-3,0) years event window; (b) whether the efficiency of acquirers improved or deteriorated post-merger over the short-term — (-1, +1), (-3, +3) years and medium-term (-3, +5) years event window. Both these questions are evaluated using financial ratio analysis as well as DEA. The study also explores if changes in efficiency scores post-merger were due to changes in scale efficiency or pure technical efficiency—evaluated through the decomposition of overall TE scores into PTE and SE; and (c) whether geographical diversification and/or changes in source of income (greater focus on interest earnings as compared to non-interest earnings) were responsible for efficiency changes post-merger—evaluated using panel Tobit regression analysis.

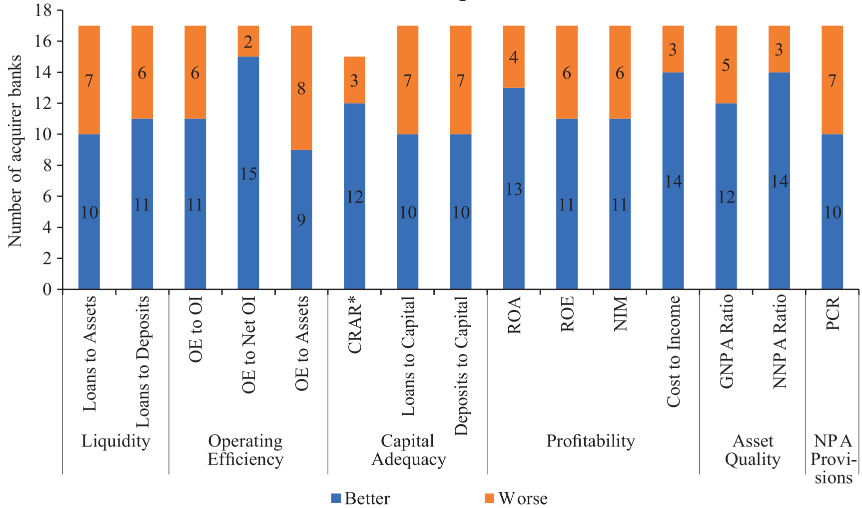
The second part is devoted to the analysis of bank mergers during 2019-2020 using event study analysis, as post-merger longer time series financial data in line with the current research design is still not available. However, we have extended the financial ratio analysis as well as the efficiency analysis for as much time period as possible.

V.1 Were the acquirers more efficient than their acquirees, pre-merger?

Theoretically, a financially sound and more efficient bank should acquire a weak and inefficient bank as that would lead to an increase in the overall efficiency of the banking system (Avkiran, 2006). The findings of some studies in the Indian context, however, suggest that government-led mergers were aimed at accommodating less efficient banks, which did not improve the overall efficiency (Das and Kumbhakar, 2022). Using bank mergers during 1997-2017, we analyse the question in the Indian context.

Using the financial ratio analysis, we find that acquirers, across all the metrics, on an average, had better financial health as compared to their acquirees in the pre-merger period (Chart 1).

Chart 1: Pre-Merger (-3,0) Financial Performance of Acquirers *vis à vis* Acquirees



Note: *: Due to unavailability of consistent data on risk weighted assets, average CRAR for entire pre-merger period could not be calculated. Instead, CRARs for (-3) was compared between acquirers and acquirees. Also, CRAR for two acquiree banks was unavailable.
Source: STRBI, Authors' calculations.

To extend the analysis through DEA, we compare the pre-merger (*i.e.,* three years before the merger year) mean[11] TE scores of acquirers to that of their acquirees. In most cases, the acquirers were found to be more efficient than their acquirees in the pre-merger period (Chart 2).

On an average, acquirers were 4 per cent more technically efficient than acquirees in the pre-merger period. Parametric (t-test and bootstrap t-test) and non-parametric (Mann-Whitney [Wilcoxon Rank-Sum]) test results confirm the findings that the mean difference between acquirers' and acquirees' TE is statistically significant (Table 4).

Presumably, most of the mergers amongst PVBs were market-driven and those between PSBs were government-led mergers. Our analysis suggests that the efficiency trends between acquirers and their acquirees were consistent across ownership patterns. Therefore, signalling out the government-led

[11] The mean efficiency scores are computed as the average efficiency scores across the four DEA models considered under the study.

Chart 2: Pre-Merger (-3,0) Mean TE of Acquirers *vis à vis* Acquirees

Note: Green coloured bars indicate that acquirers had higher TE scores than their acquirees and *vice-versa* for red bars.
Source: Authors' calculations.

mergers alone as being aimed at accommodating weak banks with stronger ones may not be correct.

V.2 Did the acquirers perform better post-merger?

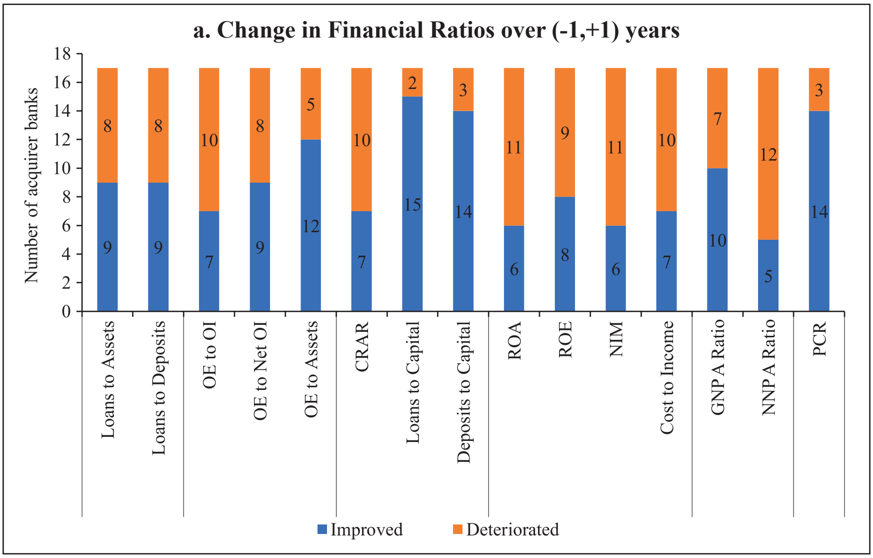
Financial ratio analysis suggests that while mergers led to improvement in acquirers' efficiency across most of the metrics, it was most prominent for liquidity, capital adequacy, profitability and NPA provisions measures.

Table 4: Acquirer *vs* Acquiree Mean TE Pre-Merger

Individual Tests	**Test groups**					
	Parametric Test				**Non-Parametric Test**	
	T-test		**Bootstrap t-test**		**Mann- Whitney [Wilcoxon Rank-Sum] test**	
Hypothesis	$P(T \leq t)$		$P(T \leq t)$		$P(Z \leq z)$	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Pre-Merger (-3,0)						
Acquiree	86.29	-2.233**	86.29	-2.263**	13.94	-2.084**
Acquirer	90.88		90.88		21.06	

Moreover, the impact was sharper in the medium term (-3 to +5 years period) as compared to the short-term (-1 to +1 years or -3 to +3 years period) (Chart 3). Gains in liquidity indicators suggest that post-merger, the

Chart 3: Impact on Financial Ratios of Acquirers Post-Merger *(Contd.)*



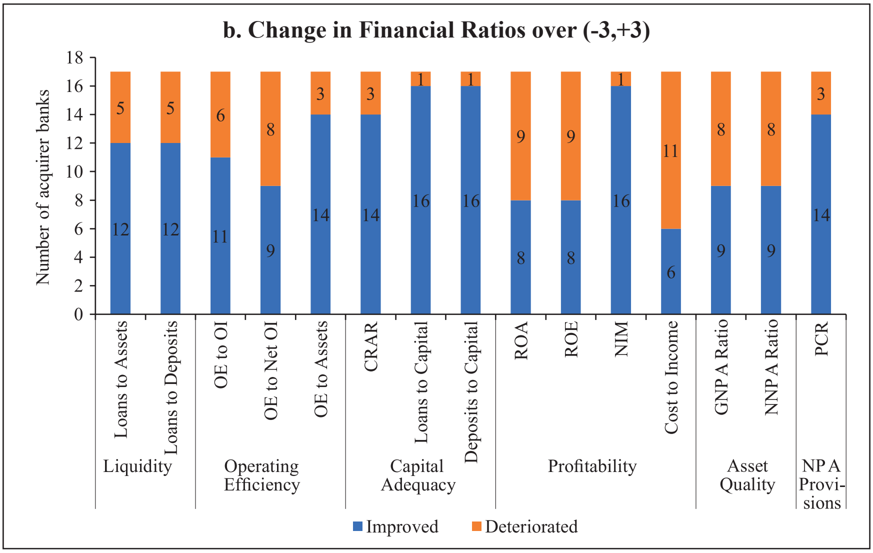
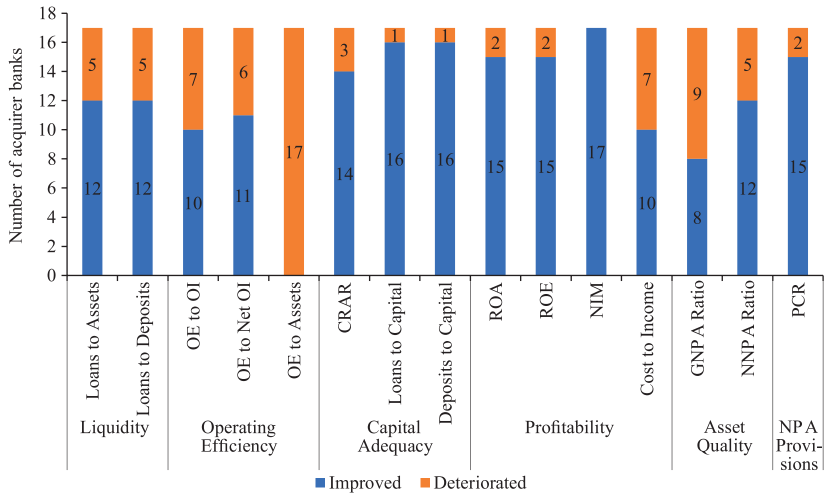


Chart 3: Impact on Financial Ratios of Acquirers Post-Merger *(Concld.)*

c. Change in Financial Ratios over (-3,+5)



Note: Due to unavailability of consistent data on RWA, average CRAR for entire pre/post merger period could not be calculated. Instead, CRAR for (-1) is compared with CRAR of (+1) and so on.

Source: Authors' calculations.

intermediation function of the combined entity improved—banks were able to channelise higher share of deposits/assets into loans. The improvement in capital adequacy and NPA provisions measures indicate that post-merger, the combined entity has become relatively more resilient to financial risks. The improvement in profitability ratios may be indicative of economies of scale—post-merger, banks may have been able to cut some operating costs by consolidating bank branches/ATMs operating in the same area, *etc.* These gains were also complemented by improvement in operating efficiency as well as asset quality indicators.

One drawback of comparing the post-merger financial ratios of the acquirer with its own pre-merger ratios is that such a comparison ignores changing macroeconomic circumstances. For example, it could be argued that during the three/ five-year period under consideration, the credit cycle may have turned, thus making all the banks more profitable and the merger may not have had a significant role to play. In order to address this issue, comparison of the acquirer with industry average performance is suggested in the literature (DeLong, 2003b). Following this method, we calculate how far the financial ratios of acquirers were in comparison to the industry average, pre-and post-merger. The findings of this exercise corroborate the earlier findings—across most metrics, the acquirers' financial performance improved post-merger compared to pre-merger, even after adjusting for industry-wide influences, both in the short-term and medium-term period (Chart 4).

Acknowledging the criticism on financial ratio analysis, it was complemented by DEA output-oriented mean TE scores for acquirer banks over the short term — (-1, +1), (-3, +3) and medium-term (-3,5) event window (Chart 5). In line with the findings of financial ratio analysis, the DEA findings suggest that the efficiency of acquirers increased post-merger—the mean TE increased from 90.88 in the pre-merger period to 93.80 three years

Chart 4: Impact on Industry-Adjusted Financial Ratios of Acquirers Post-Merger *(Contd.)*

a. Change in Industry-Adjusted Financial Ratios over (-1,+1) years

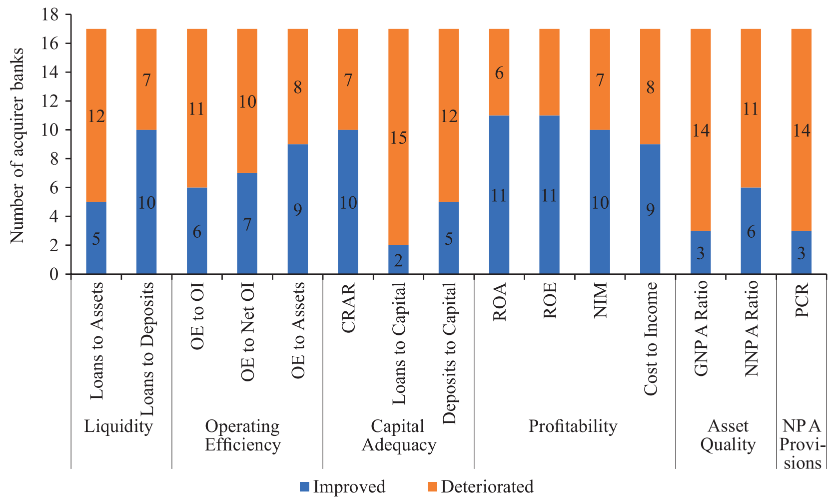
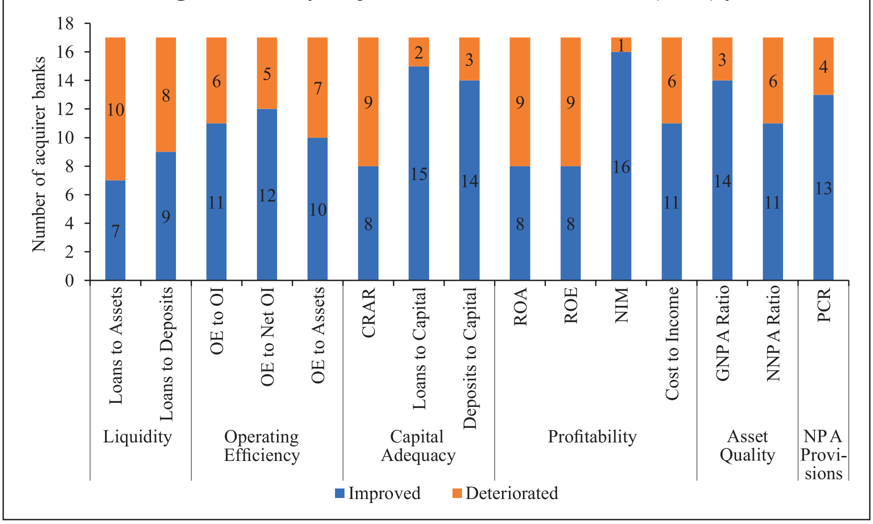
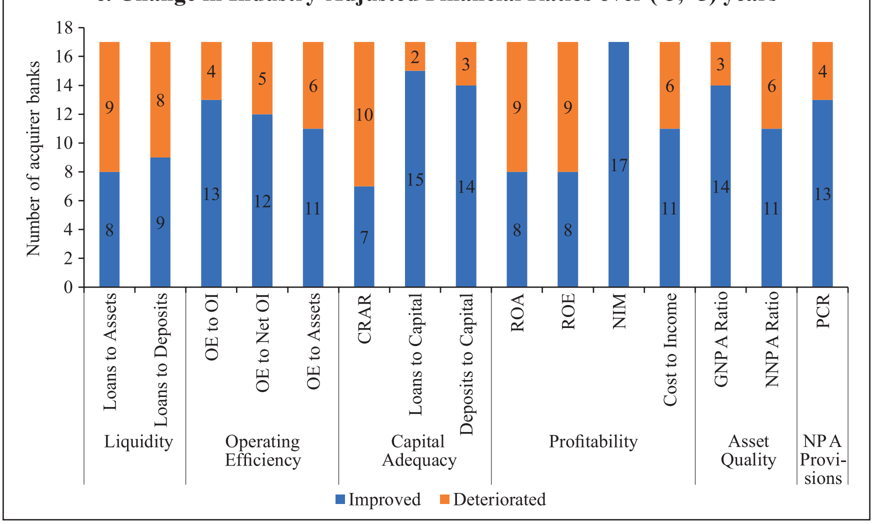


Chart 4: Impact on Industry-Adjusted Financial Ratios of Acquirers Post-Merger *(Concld.)*



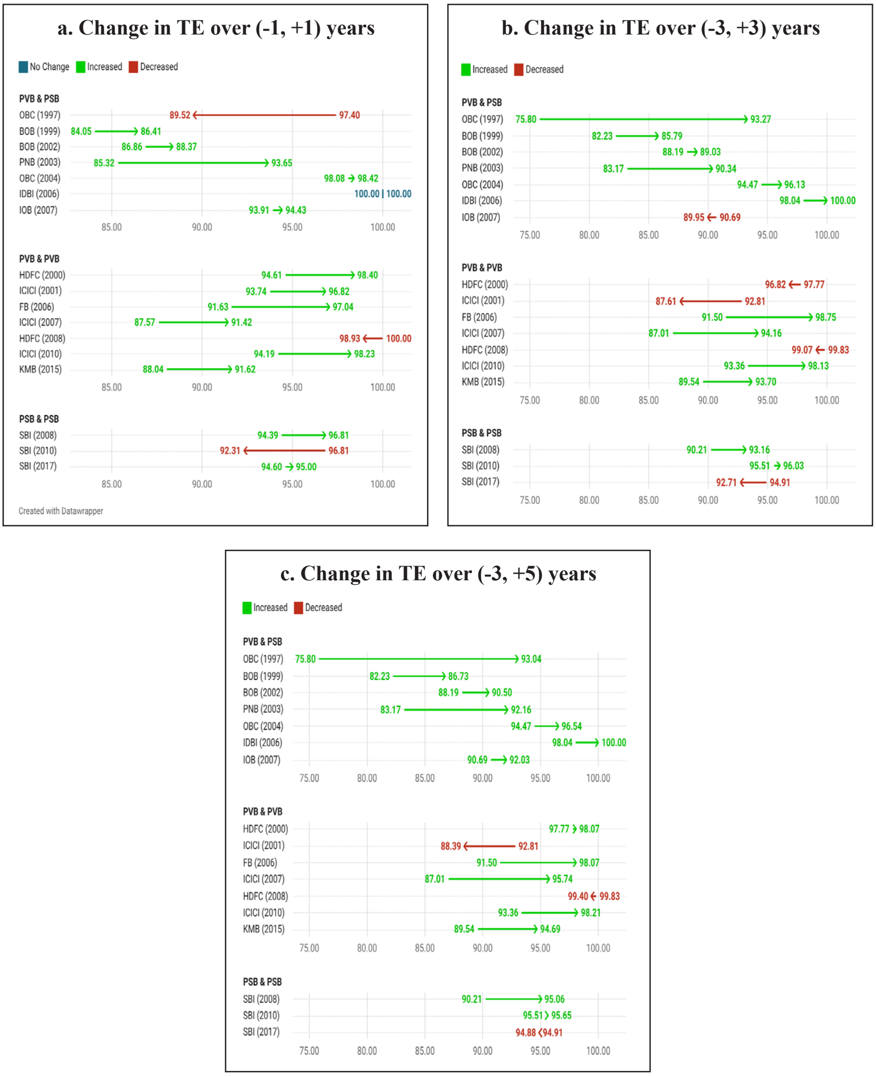


Note: Due to unavailability of consistent data on RWA, average CRAR for entire pre/post merger period could not be calculated. Instead, CRAR for (-1) is compared with CRAR of (+1) and so on.

Source: Authors' calculations.

post-merger and 94.24 five years post-merger. In other words, the average inefficiency[12] of acquirer banks reduced from 9.12 per cent pre-merger to 6.20 per cent and 5.70 per cent, three years and five years post-merger, respectively.

Chart 5: Change in Mean TE of Acquirers Post-Merger



Source: Authors' calculations.

12 Inefficiency score can be computed as (1-efficiency) score (Isik, 2002).

Table 5: Acquirer's Mean TE Pre- and Post-Merger

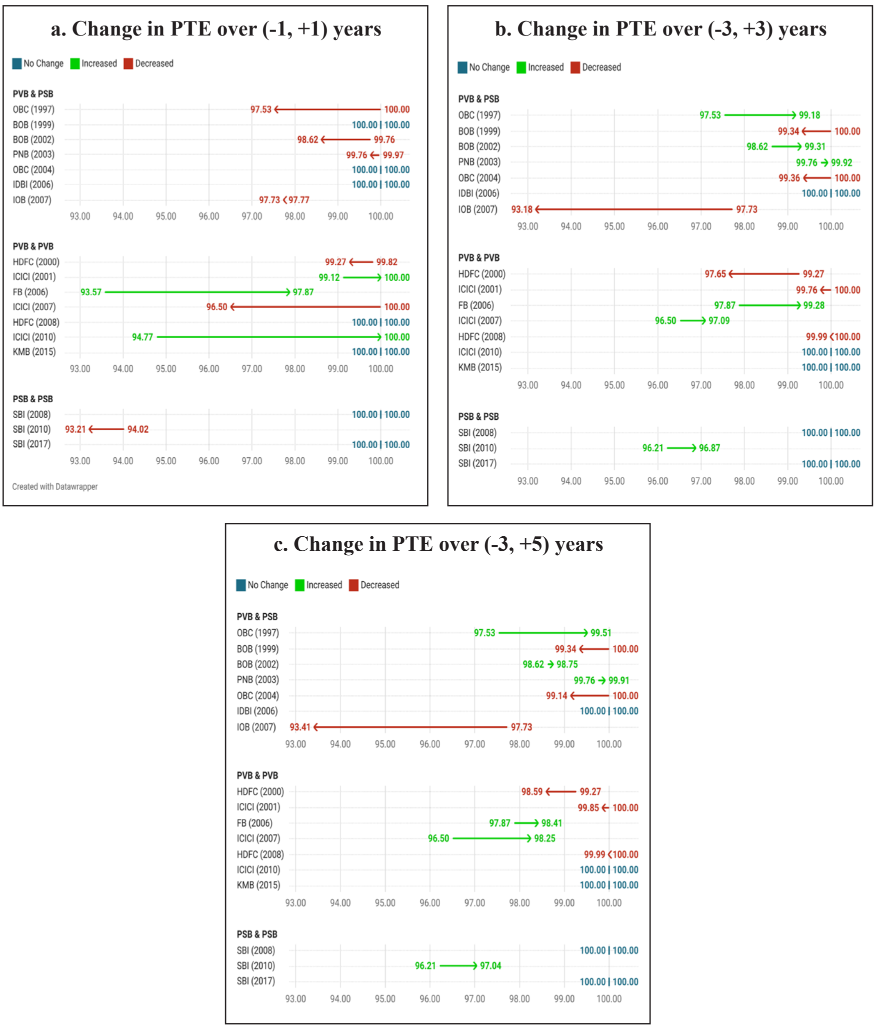
Individual tests	**Test groups**					
	Parametric Test				**Non-Parametric Test**	
	t-test		**Bootstrap t-test**		**Wilcoxon Signed-Rank Test**	
Hypothesis	P(T ≤ t)		P(T ≤ t)		P(Z ≤ z)	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Short-term event window (-1,1)						
Pre-merger	93.01	-1.697	93.01	-1.759	15.97	-2.343**
Post-merger	94.55		94.55		19.03	
Short-term event window (-3,3)						
Pre-merger	90.88	-2.471**	90.88	-2.573**	15.29	-2.231**
Post-merger	93.80		93.80		19.71	
Medium-term event window (-3,5)						
Pre-merger	90.88	-3.172*	90.88	-3.266**	14.68	-2.397**
Post-merger	94.24		94.24		20.32	

The results are statistically significant (Table 5). This improvement can be attributed to improvement in banks' ability to curtail cost-inefficiency and better management practices.

The results of the paper that mergers have, on an average, led to improvement in efficiency gains of acquirer banks are in contrast with the findings of Das and Kumbhakar (2022). This is partly due to methodological differences; while they used SFA, we used DEA. More importantly, however, their analysis focuses on the point that the acquired banks were more inefficient as compared with their acquirers. From this, they conclude that merger of inefficient banks with the more efficient banks may have pulled down the efficiency of the merged entity. While the present paper agrees with the findings of Das and Kumbhakar (2022) that typically the acquired entities were more inefficient than their acquirers, we show that this has not necessarily affected the efficiency of the merged entity. In section V.3, we show that, in fact geographical diversification and more focus on net interest income as earning source have improved the efficiency of the merged bank.

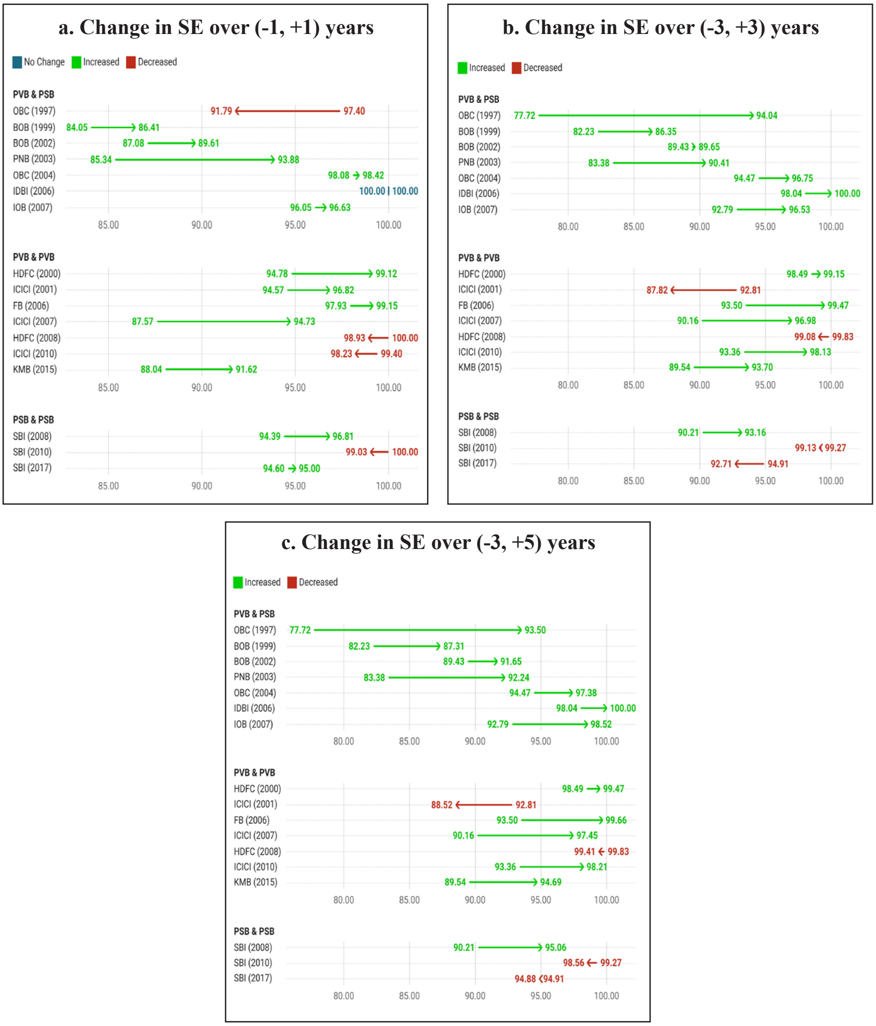
Decomposing the post-merger TE scores into PTE and SE, the results indicate that the mean PTE of acquirers changed marginally from 98.85 in the pre-merger period to 98.82 three years post-merger and 98.85 five years post-merger. On the other hand, the mean SE of acquirers improved significantly from 92.11 in the pre-merger period to 95.15 three years post-merger and 95.37 five years post-merger (Chart 6 and Chart 7). These results, taken together indicate that relatively weak and inefficient

Chart 6: Change in Mean PTE of Acquirers Post-Merger



Source: Authors' calculations.

Chart 7: Change in Mean SE of Acquirers Post-Merger



Source: Authors' calculations.

acquiree banks were not a hindrance for efficiency of the merged entity and acquirers benefited from mergers primarily on account of increased scale of productive capacity.

The test results for PTE and SE scores also confirm the finding that there is no statistically significant difference in the pure technical efficiency of acquirer banks post-merger whereas the improvement in scale efficiency is statistically significant, both over the short-term and medium-term event window (Table 6 and Table 7).

V.3: Does geographical diversification or focus on interest income explain efficiency gains?

In order to investigate factors that may explain the efficiency improvement, a novel approach of panel-data Tobit regression was adopted with TE scores of acquirers as the dependant variable:

$$TE_{bt} = \alpha + \beta_1 . GC_{bt} + \beta_2 . (NII/TI)_{bt} + \gamma . size_{bt} + \delta . bank\ group\ dummy + \mu_i + \epsilon_{it}$$

where, GC is geographical concentration and NII/TI is the share of non-interest income to total income.[13] Using state-wise branch spread of acquirers before and after merger, we constructed the Herfindahl-Hirschman index (HHI) of geographical concentration (GC). Thus, if the banks' branches were

Table 6: Acquirer's Mean PTE Pre- and Post-Merger

Individual tests	Test groups					
	Parametric Test				Non-Parametric Test	
	t-test		Bootstrap t-test		Wilcoxon Signed-Rank Test	
Hypothesis	P(T ≤ t)		P(T ≤ t)		P(Z ≤ z)	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Short-term event window (-1,1)						
Pre-merger	98.75	-0.200	98.75	-0.205	17.76	0.267
Post-merger	98.85		98.85		17.24	
Short-term event window (-3,3)						
Pre-merger	98.85	0.088	98.85	0.090	18.21	0.351
Post-merger	98.82		98.82		16.79	
Medium-term event window (-3,5)						
Pre-merger	98.85	-0.258	98.85	-0.265	17.71	0.106
Post-merger	98.95		98.95		17.29	

13 Given the lack of large sample size, the regression model is kept parsimonious, with only two crucial bank specific explanatory variables. The bank size is used to assess the differences in efficiency improvements between large and small banks. Similarly, bank group dummy is added to compare differences in efficiency improvements between PSB and PVB group.

Table 7: Acquirer's Mean SE Pre- and Post-Merger

Individual tests	**Test groups**					
	Parametric Test				**Non-Parametric Test**	
	t-test		**Bootstrap t-test**		**Wilcoxon Signed-Rank Test**	
Hypothesis	P(T ≤ t)		P(T ≤ t)		P(Z ≤ z)	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Short-term event window (-1,1)						
Pre-merger	94.78	-0.964	92.11	-0.994	16.44	-1.086
Post-merger	95.73		95.15		18.56	
Short-term event window (-3,3)						
Pre-merger	91.96	-2.554**	91.96	-2.645**	15.47	-2.296**
Post-merger	94.95		94.95		19.53	
Medium-term event window (-3,5)						
Pre-merger	91.96	-2.647**	92.11	-2.747**	15.29	-2.462**
Post-merger	95.25		95.37		19.71	

concentrated in a few states, it gave a relatively higher HHI score as compared to a bank whose branches are spread widely across many states. An eyeball analysis suggests that the HHI of acquirer generally declined post-merger, implying that their geographical concentration reduced. Termed differently, merger resulted in geographical diversification for the acquirers.

Elyasiani *et al.* (2012) used data on lending, securities and insurance activities of Bank Holding Companies (BHCs) to measure changes in production efficiency and found a negative association of TE with activity diversification. Data constraints however prevent us from using the same. Instead, we use the ratio of non-interest income to total income (NII/TI) as a proxy. The rationale behind this is that the primary business of banks is lending and any change in strategy that increases the share of interest income in total income may lead to increase in its efficiency. The expected sign of coefficient of this variable is negative. Apart from these factors, size of the bank (proxied by log of total assets) and a bank group dummy (0 for PSBs and 1 for PVBs) are used as control variables.

Table 8: Random Effects Tobit Regression for Acquirer's TE over (-3,3)

Dependent Variable: TE (-3,3)				
	(1)	(2)	(3)	(4)
GC	-.303*** (.117)	-.344*** (.117)		-.326*** (.12)
Share of NII/TI	-.002 (.001)		-.003** (.001)	-.002 (.001)
Size	0 (.006)	.002 (.006)	.01** (.005)	.001 (.006)
Bank Group dummy	.053* (.028)	.044 (.028)	.044** (.022)	
Constant	.991*** (.08)	.994*** (.082)	.844*** (.058)	1.018*** (.083)
Observations	102	102	102	102
AIC	-314.06	-313.70	-307.94	-312.71

Note: 1. *** p<.01, ** p<.05, *p<.1

2. Figures in the parenthesis represent standard errors.

3. All the covariates are winsorised at the 95th percentile.

4. The TE scores were scaled down to lie between [0,1].

Source: Authors' calculations.

The results indicate that post-merger geographical diversification and an increase in the share of interest income to total income led to improvement in efficiency. In particular, the negative coefficient of GC suggests that post-merger reduction in geographical concentration explains efficiency gains. Also given that the banking business is primarily focussed on lending activities, the diversification of banks away from non-interest income to interest income may have contributed to increased efficiencies (Table 8).

The results are consistent across short-term as well as medium-term period (Table 9). In addition, the positive coefficient of asset size variable suggests that an increase in asset size post-merger helped in strengthening efficiencies. Gains in efficiencies were significantly higher for PVBs as compared with their PSB counterparts.

V.4 How did the recent bank mergers perform?

Since the recent spate of banking mergers (*i.e.*, bank mergers during 2019-2020; refer to Annex II for details) attracted a lot of attention from analysts and researchers, we extended the analysis for these mergers as well, although longer time-series post-merger data as used in the earlier exercise

Table 9: Random Effects Tobit Regression for Acquirer's TE over (-3,5)

Dependent Variable: TE (-3,5)				
	(1)	(2)	(3)	(4)
GC	-.164** (.078)	-.19** (.079)		-.172** (.082)
Share of NII/TI	-.003*** (.001)		-.003*** (.001)	-.002** (.001)
Size	.007 (.005)	.006 (.005)	.014*** (.004)	.007 (.005)
Bank Group dummy	.048** (.022)	.034 (.022)	.044** (.02)	
Constant	.9*** (.069)	.88*** (.07)	.804*** (.051)	.915*** (.072)
Observations	136	136	136	136
AIC	-439.34	-434.61	-436.67	-434.45

Note: 1. *** p<.01, ** p<.05, *p<.1
2. Figures in the parenthesis represent standard errors.
3. All the covariates are winsorised at the 95th percentile.
4. The TE scores were scaled down to lie between [0,1].

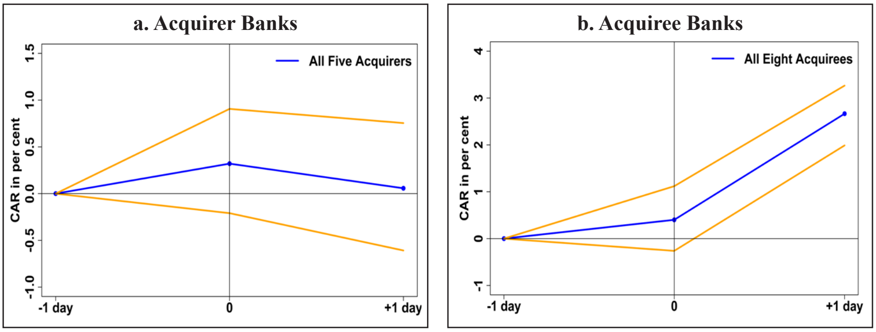
Source: Authors' calculations.

is not yet available. Given that all the banks involved in the recent mergers were publicly listed, it is possible to evaluate the impact on shareholders' wealth using the event study framework. An analysis of cumulative abnormal returns (CARs) one day prior and one day after the 'news leak day' suggested wealth gain for shareholders of the acquiree banks but losses for shareholders of the acquirer banks.[14] This is not surprising in light of our earlier result that generally weak banks are acquired by stronger banks. Thus, the markets viewed the news of merger positively for the acquiree banks—in anticipation that their financials would strengthen after merger—but negatively for acquirer banks (Chart 8).

Although longer time series data is not yet available for bank mergers between 2019-2020, the event study is complemented with financial ratio

[14] For example, the news of merger of 10 PSBs into four was announced by the Finance Minister in a press conference on August 30, 2019 after trading hours. Since the morning of August 30, 2022, however, news that a mega-merger of banks is in the offing was trending on the internet, suggesting that the markets had already priced-in the news before it was formally announced. To take into account this price variation in our analysis, August 28, 2019 is treated as the neutral day and price variation from August 29 to August 30 are treated as 'announcement effect'.

Chart 8: CARs for the Acquirer and Acquiree Banks



Note: In line with Houston and Ryngaert (1994) and Houston *et al.* (2001), the event considered under the study is based on date of leak *i.e.,* one day prior to the actual announcement day. The orange coloured lines represent the 95% bootstrapped confidence interval.
Source: Authors' calculations.

analysis and DEA using the data available so far. Financial ratio analysis suggests that CRAR, RoA, RoE, cost-to-income ratio, GNPA, NNPA and NPA provisions improved for the acquirers, post-merger (Chart 9). Moreover, the results are consistent across most of the metrics even after adjusting for industry-wide influences (Chart 10).

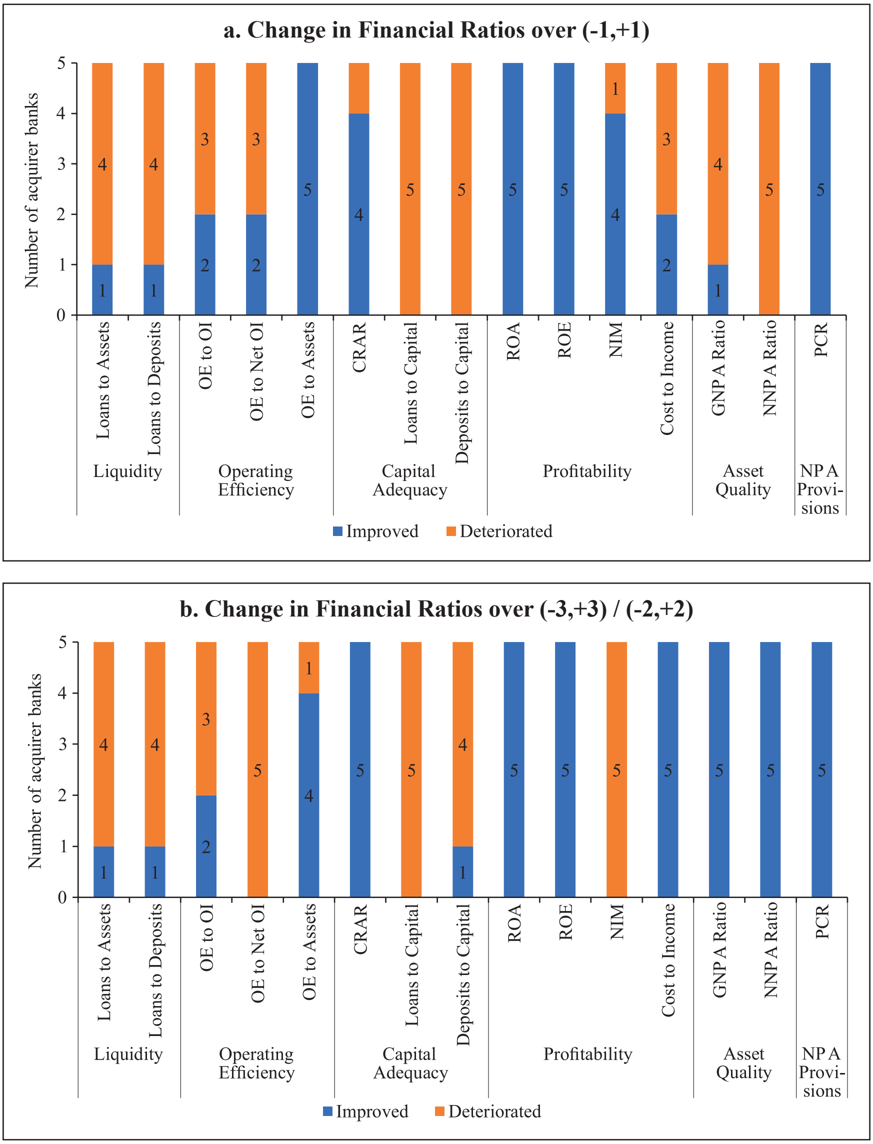
Using limited data available so far, DEA analysis suggests that in four out of five cases under the study, acquirers were more efficient than the acquirees—in line with the historical trend presented earlier (Table 10). Test results of parametric and non-parametric tests also confirm that the differences in their efficiency are statistically significant (Table 11).

Table 10: Acquirer's *vs* Acquiree's Technical Efficiency Pre-Merger

Merger	Pre-Merger						Acquirer's Pre-merger Average	Acquiree's Pre-merger Average	If Acquirer More Efficient than Acquiree Pre-Merger
	Acquirer			Acquiree					
	3 years	2 years	1 year	3 years	2 years	1 year			
Merger 1	97.24	98.65	99.31	92.03	90.58	94.00	98.40	92.20	Yes
Merger 2	99.73	90.79	97.55	96.88	93.52	95.63	96.02	95.34	Yes
Merger 3	92.33	92.68	95.52	90.23	90.21	82.70	93.51	87.71	Yes
Merger 4	94.96	96.19	96.86	90.79	87.91	90.84	96.00	89.85	Yes
Merger 5	96.94	96.44	97.12	97.77	99.35	96.97	96.83	98.03	No

Note: In order to protect the financial interests of entities involved, mergers are neither arranged chronologically, nor alphabetically in this table, but randomly.

Chart 9: Impact on Financial Ratios of Acquirers Post-Merger



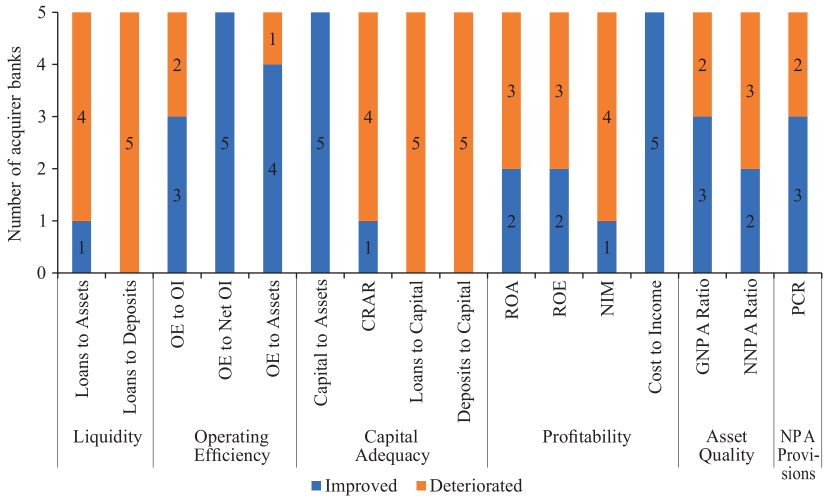
Note: Based on the availability of post-merger data, financial ratios for Bank of Baroda have been compared over (-3,3) and other banks are compared over (-2,2) years.

Source: Authors' calculations

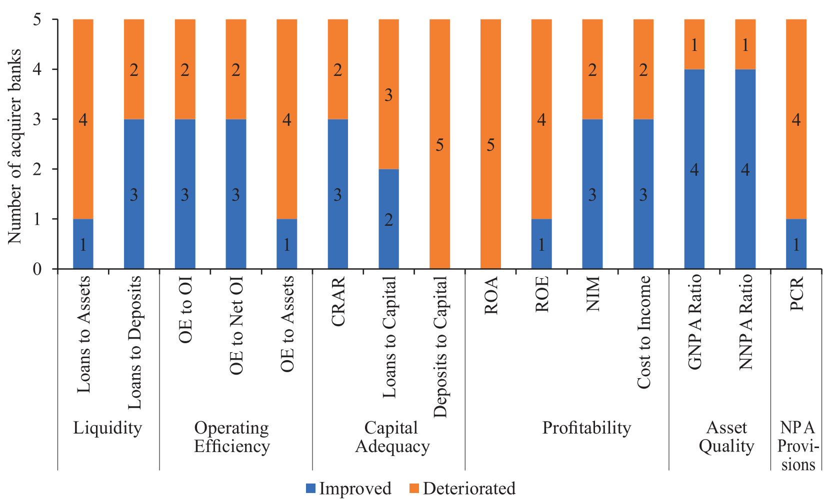
The DEA results also show that in most of the cases, the efficiency of acquirer has improved post-merger, and the difference is statistically significant (Tables 12 and 13). It may be noted that the results are based on

Chart 10: Impact on Industry-Adjusted Financial Ratios of Acquirers Post-Merger

a. Industry-Adjusted Financial Ratios over (-1,+1)



b. Industry-Adjusted Financial Ratios over (-3,+3) / (-2,+2)



Note: Based on the availability of post-merger data, financial ratios for Bank of Baroda have been compared over (-3,3) and other banks are compared over (-2,2) years.

Source: Authors' calculations.

limited data available so far and it is acknowledged that efficiency gains in some cases are yet to accrue and reflect in financial performance completely.

Notwithstanding this disclaimer, it can be argued that recent mergers in the banking sector have contributed to efficiency gains.

Table 11: Acquirer's *vs* Acquiree's Mean TE Pre-merger

Individual tests	**Test groups**					
	Parametric Test				**Non-Parametric Test**	
	T-test		**Bootstrap t-test**		**Mann- Whitney [Wilcoxon Rank-Sum] test**	
Hypothesis	$P(T \leq t)$		$P(T \leq t)$		$P(Z \leq z)$	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Pre-Merger (-3,0)						
Acquiree	92.63	-1.750*	92.63	-1.830*	4	-1.462*
Acquirer	96.15		96.15		7	

Table 12: Acquirer TE Post-Merger

	Pre-merger			**Post-merger**			**Pre-merger Average**	**Post-merger Average**	**Change in Efficiency**
	3 years	**2 years**	**1 year**	**1 year**	**2 years**	**3 years**			
Merger 1	94.96	96.19	96.86	92.28	93.06	88.13	96.00	91.16	Decreased
Merger 2		90.79	97.55	96.54	98.46		94.17	97.50	Increased
Merger 3		92.68	95.52	93.55	98.13		94.10	95.84	Increased
Merger 4		96.44	97.12	96.57	98.12		96.78	97.34	Increased
Merger 5		98.65	99.31	96.25	96.52		98.98	96.39	Decreased

Note:1. In order to protect the financial interests of entities involved, mergers are neither arranged chronologically nor alphabetically in this table, but randomly.
2. Based on the availability of post-merger data, financial ratios for Bank of Baroda have been compared over (-3,3) and other banks are compared over (-2,2) years.

Source: Authors' calculations.

Table 13: Acquirer's Mean TE Pre- and Post-Merger

Individual tests	**Test groups**					
	Parametric Test				**Non-Parametric Test**	
	t-test		**Bootstrap t-test**		**Wilcoxon Signed-Rank Test**	
Hypothesis	$P(T \leq t)$		$P(T \leq t)$		$P(Z \leq z)$	
Test Statistics	Mean	t	Mean	t	Mean rank	z
Pre-merger	96.01	0.243	96.01	0.272	5.4	-0.135
Post-merger	95.65		95.65		5.6	

Section VI
Conclusions

Compiling data on bank mergers during 1997-2020, comprising both public and private sector banks, the current study employs DEA, financial ratio technique and event study analysis to investigate the impact of bank mergers in the Indian context. The study also uses a novel technique of panel Tobit regression to assess the factors that may have contributed to efficiency gains in the post-merger period. In particular, the paper seeks to answer four questions: a) What were the efficiency characteristics of acquirer and acquiree banks pre-merger? In particular, whether the mergers were amongst equals or between a strong and a weak bank?; b) Whether the financial performance and efficiency of acquirers improved or deteriorated post-merger and what contributed to these efficiency gains – improvement in managerial prowess or scale efficiencies?; c) Did geographical diversification and/or greater focus on interest earnings post-merger contribute to efficiency improvement?; and d) How successful were the recent mergers?

The findings of the paper confirm that banking mergers in India have been, on an average, beneficial to the banking sector as the financial performance and efficiency of acquirers improved post-merger. These findings also hold true for the recent bank mergers during 2019-2020, for which limited data is available so far. Our findings suggest that the mean technical efficiency of acquirers increased from 90.88 in the pre-merger period to 93.80 three years post-merger, and 94.24 five years post-merger. Relatively lower managerial and organisational competencies in acquired banks were not a hindrance for preserving efficiency of the merged entity and the benefits to acquirers from mergers on account of increased scale of productive capacity were statistically significant. A deep dive into factors that may have led to efficiency gains identifies post-merger geographical diversification and improvement in the share of interest income as the significant factors.

An analysis of cumulative abnormal returns one day prior and one day after the 'news leak day' in the event study framework for banks that merged during 2019-2020 suggested wealth gains for the shareholders of the acquiree banks. This is not surprising in light of our earlier results that generally weak banks were acquired by stronger banks. Thus, the markets viewed the news of merger positively for the acquiree banks, in anticipation that their financials would strengthen after merger.

The evidence so far, thus, suggests that mergers have been an effective tool of efficiency improvement in the Indian banking sector. Mergers have provided avenues for increasing the scale of operations, geographical diversification, and adoption of more efficient business strategies.

References

Akhavein, J., Berger, A., & Humphrey, D. (1997). The effects of megamergers on efficiency and prices: evidence from a bank profit function. *12(1)*, 95–139.

Alexander, W. R. J., & Joforullah, M. (2005). Scale and pure efficiencies of New Zealand secondary schools. (Discussion Paper No. 0501). University of Otago.

Al-Sharkas, A., & Hassan, M. (2010). New evidence on shareholder wealth effects in bank mergers during 1980–2000. *34(3)*, 326-348.

Al-Sharkas, A., Hassan , M., & Lawrence, S. (2008). The impact of mergers and acquisition on the efficiency of the US banking industry: further evidence. *35(1/2)*, 50-70.

Amihud, Y., DeLong, G., & Saunders, A. (2002). The effects of cross-border bank mergers on bank risk and value. *J Int Money Financ, 21(6)*, 857-877.

Antil, S., Kumar, M. & Swain, N. (2020) Evaluating the efficiency of regional rural banks across the Indian states during different phases of structural development, *Applied Economics*, 52:41, 4457-4473.

Avkiran, N. (1999). The evidence on efficiency gains: the role of mergers and the benefits to the public. *Journal of Banking and Finance*, 23, 991-1013..

Avkiran, N.K. (2006). Productivity analysis in the service sector with Data Envelopment Analysis. Available at SSRN: https://ssrn.com/abstract=2627576

Azofra, S., Olalla, M., & Olmo, B. (2008). Size, Target Performance and European Bank Mergers and Acquisitions. *American Journal of Business*, 53-63.

Bauer, P. W., Berger, A. N., Hamphrey, D.B., & Ferrier, G.D. (1998). Consistency conditions for regulatory analysis of financial institutions. *Journal of Economics and Business, 50*, 85-114.

Benston, G. J. (1965). Branch Banking and Economies of Scale. *The Journal of Finance* 20 (2): 312–331.

Berger, A. N., Saunders , A., Scalise , J. M., & Udell , G. F. (1998). The effects of bank mergers and acquisitions on small business lending. *Journal of Financial Economics* , 187-229.

Bhattacharyya, A., Lovell, C., & Sahay, P. (1997). The impact of liberalization on the productive efficiency of Indian commercial banks. *European Journal of Operational Research, Elsevier, vol. 98(2), pages 332-345, April*.

Bishnoi, R. T., & Devi, S. (2015). Mergers and Acquisitions of Banks in Post-Reform India. *Economic and Political Weekly* , 50-58.

Boyd, J., H., Graham, S., L. (1988) The profitability and risk effects of allowing bank holding companies to merge with other financial firms: a simulation study. *Fed Reserve Bank Minneap Q Rev* 12(2):3–20.

Campa J., M., Hernando, I. (2006) M&As performance in the European financial industry. *J Bank Financ* 30(12):3367–3392.

Chen, Y. & Ali, I., A. (2002). Output-input ratio analysis and DEA frontier. *European Journal of Operational Research*, Elsevier, vol. 142(3), pages 476-479, November.

Cornett, M., & Tehranian, H. (1992). Changes in corporate performance associated with bank acquisitions. *J Financ Econ, 31(2)*, 211–234.

Cornett, M. M., McNutt, J. J., & Tehranian, H. (2006). Performance Changes around Bank Mergers: Revenue Enhancements versus Cost Reductions. *Journal of Money, Credit and Banking*, 38(4), 1013–1050.

Das, A., Kumbhakar, S., C. (2022). Bank Merger, Credit Growth, and the Great Slowdown in India. Economic and Political Weekly, Volume 57, Year 2022, Pages 58-67.

DeLong, G. (2003a). The announcement effects of US versus non-US bank mergers: do they differ? *J Financ Re, 26(4)*, 487–500.

DeLong. (2003b). Does long-term performance of mergers match market expectations? Evidence from the U.S. banking industry. *Financial Management 32, 5–25., 32*, 5-25.

DeYoung, R. (1997) Bank mergers, x-efficiency, and the market for corporate control. *Manag Financ* 23(1):32–47.

DeYoung, R., Evanoff, D., D. & Molyneux, P. (2009). Mergers and Acquisitions of Financial Institutions: A Review of the Post-2000 Literature. *J Financ Serv Res* 36, 87–110.

Elyasiani, E., & Wang, Y. (2012). Bank holding company diversification and production efficiency. *Applied Financial Economics, 22:17*, 1409-1428.

Reserve Bank of India, (2008). *Report on Currency and Finance.*.

Fixler, D., & Zieschang, K. (1993). An index number approach to measuring bank efficiency: an application to mergers. *J Bank Financ, 23(4)*, 367–386.

Fried , H., Lovell, C., & Yaisawarng, S. (1999). The impact of mergers on credit union service provision. *J Bank Financ, 23(4)*, 367–386.

Goddard, J., Molyneux, P., & Zhou, T. (2012). Bank mergers and acquisitions in emerging markets: evidence from Asia and Latin America. *Eur J Financ, 18(5)*, 419–438.

Gurkaynak, R., & Wright , J. (2013). Identification and inference using event studies. *81*, 48–65.

Hannan, T., & Wolken, J. (1989). Returns to bidders and targets in the acquisition process: evidence from the banking industry. *J Financ Serv Res,* 3(1), 5–16.

Haynes, M., & Thompson, S. (1999). The productivity effect of bank mergers: evidence from the UK building societies. *J Bank Financ , 23(5)*, 825–846.

Houston, J., & Ryngaert, M. (1994). The overall gains from large bank mergers. *J Bank Financ, 18(6)*, 1155–1176.

Houston, J., & Ryngaert, M. (1997). Equity issuance and adverse selection: a direct test using conditional stock offers. *J Financ, 52(1)*, 197–219.

Houston, J., James, C., & Ryngaert, M. (2001). Where do merger gains come from? Bank mergers from the perspective of insiders and outsiders. *J Financ Econ , 60(2/3)*, 285–331.

Isik, I., & Hassan, M. (2002). Technical, scale and allocative efficiencies of Turkish banking industry. *Journal of Banking and Finance, 26*, 719–66.

Ismail, A., & Davidson, I. (2005). Further analysis of mergers and shareholder wealth effects in European banking. *Appl Financ Econ , 15(1)*, 13–30.

Ismail, A., & Davidson, I. (2007). The determinants of target returns in European bank mergers. *Serv Ind J, 27(5)*, 617–634.

Jayaraman, A., & Srinivasan, M. R. (2014). Impact of merger and acquisition on the efficiency of Indian bank: a pre -post analysis using data envelopment analysis. *Int. J. Financial Services Management, 7 (1)*.

Joshua, O. (2011). Comparative Analysis of the Impact of Mergers and Acquisitions on Financial Efficiency of Banks in Nigeria. *Journal of Accounting and Taxation*, 3, 1-7.

Kao, C., & Liu, S. (2004). Predicting Bank Performance with Financial Forecasts: A Case of Taiwan Commercial Banks. *Journal of Banking & Finance, 28 (10)*, 2353–2368.

Kashyap, N. & Mahapatro, S. & Tantri, P. (2022). How Does The Rescue of Weak Banks Through Mergers Impact Loan Performance? Evidence From India *.

Kiymaz, H. (2004). Cross-border acquisitions of US financial institutions: impact of macroeconomic factors. *J Bank Financ, 28(6)*, 1413–1439.

Kiymaz, H. (2013). Cross-border mergers and acquisition and country risk ratings: evidence from US financials. *Int J Bus Financ Res, 7(1)*, 17–29.

Knapp, M., Gart, A. & Becher, D. (2005). Post-Merger Performance of Bank Holding Companies, 1987-1998. *The Financial Review,* Eastern Finance Association, vol. 40(4), pages 549-574, November.

Kolaric, S. & Schiereck, D. (2013). Shareholder wealth effects of bank mergers and acquisitions in Latin America. *Management Research: The Journal of the Iberoamerican Academy of Management*, 11(2), 157-177.

Kolaric, S. & Schiereck, D. (2014). Performance of bank mergers and acquisitions: a review of the recent empirical evidence. *Manag Rev Q* , 39-71.

Kondova, G., G. & Burghof, H., P. (2007) The impact of bank mergers on efficiency: empircial evidence from the German banking industry. In: Conference paper presented at the EFMA annual meeting 2007, Vienna

Kumar, M., Kumar, S. & Deisting, F. (2013). Wealth effects of bank mergers in India: A study of impact on share prices, volatility and liquidity. *Banks and Bank Systems*, 8(1), 127–133.

Kwan, S., & Wilcox, J. (1999). Hidden cost reductions in bank mergers: accounting for more productive banks. Working Papers in Applied Economic Theory 99-10, Federal Reserve Bank of San Francisco.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics, 95*, 391–413.

Leeladhar, V. (2008). Consolidation in the Indian Financial Sector. Adress at the International Banking & Finance Conference. *Indian Merchants' Chamber, Mumbai.*

Lee, T., H., Liang, L., W. & Huang, B., Y. (2013). Do mergers improve the efficiency of banks in Taiwan? Evidence from stochastic frontier approach. *The Journal of Developing Areas*, 47(1), 395–416.

Linder, J. & Crane, D. (1993). Bank mergers: integration and profitability. *J Financ Serv Res, 7(1)*, 35–55.

Liu , B. & Tripe, D. (2003). New Zealand Bank Mergers and Efficiency Gains. *Journal of Asia-Pacific Business*, 37-41.

MacKinlay, A. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, 35(1)*, 13–39.

Mathur, A., Sengupta, R. & Pratap, B. (2021). Saved by the bell? Equity market responses to surprise Covid-19 lockdowns and central bank interventions. .

Mester, L. (1987). Efficient production of financial services: scale and scope economies. *Federal Reserve Bank of Philadelphia Business Review*, 15-25.

Nataraja, N., R., & Johnson, A., L. (2011). Guidelines for Using Variable Selection Techniques in Data Envelopment Analysis. *European Journal of Operational Research, 215 (3)*, 662–669.

Neyman, J., & Scott, E. (1948). Consistent Estimates Based on Partially Consistent Observations. *Econometrica, 16*, 1-32.

Nishat, Shabnam, The Impact of Mega Mergers on the Efficiency of Indian PSU Banks (March 22, 2020). IUP *Journal of Business Strategy*. Jun2020, Vol. 17 Issue 2, p21-33. 13p

Peristiani, S. (1997). Do mergers improve the x-efficiency and scale efficiency of US banks? Evidence from the 1980s. *J Money Credit Bank , 29(3)*, 326–337.

Reda, M. (2013). The effect of mergers and acquisitions on bank efficiency: evidence from bank consolidation in egypt. *The Economic Research Forum (ERF)*, 1-24.

Rhoades, S. (1998). The efficiency effects of bank mergers: An overview of case studies of nine mergers. *Journal of Banking and Finance*, 22, 273–291.

Sameer Mohammed Sindi & A.N. Bany-Ariffin & Nazrul Hisyam Ab Razak & Fakarudin Kamarudin. (2021). Bank mergers and acquisitions in emerging markets: evidence from the Middle East and the North Africa region, *International Journal of Business and Globalisation*, vol. 28(1/2), pages 97-116.

Sathye, M. (2001). X-efficiency in Australian banking: An empirical investigation. Journal of Banking and Finance. *Journal of Banking and Finance, 25*, 613–630.

Sathye, M. (2003). Efficiency of Banks in a Developing Economy: The Case of India. *European Journal of Operational Research, 148 (3)*, 662–671.

Schiereck, S. K. (2014, January). Performance of bank mergers and acquisitions: a review of the recent emprical evidence. 39-71. doi:10.1007/s11301-014-0099-3

Seadly, C., & Lindley , J. (1977). Inputs, outputs and a theory of production and cost at depository financial institutions. *Journal of Finance, 32*, 1251±1266.

Singh, P. (2009). Mergers in Indian Banking: Impact Study using DEA Analysis. *South Asian journal of management*. Vol. 16.2009, 2, p. 7-27.

Sonia Antil, Mukesh Kumar & Niranjan Swain. (2020). Evaluating the efficiency of regional rural banks across the Indian states during different phases of structural development, *Applied Economics*, 52:41, 4457-4473,

Sufian, F., & Habibullah, M. (2009). Asian financial crisis and the evolution of Korean banks efficiency: A DEA approach. *Global Economic Review, Taylor and Francis Journals, 38 (4)*, 335-69.

Sufian, F. (2007). Mergers and acquisitions in the Malaysian banking industry: technical and scale efficiency effects. *International Journal of Financial Services Management* , 304-326.

Thanassoulis, E., Boussofiane, A., & Dyson, R. (1996, June). A comparison of data envelopment analysis and ratio analysis as tools for performance assessment. *Omega, Elsevier, 24 (3)*, 229-244.

Wanke, M. G. (2017). Merger and acquisitions in South African banking: A network DEA model. *Research in International Business and Finance*, 362-376.

Annexure

Annex I: List of M&As during 1997-2017

Sr. No.	Name of Transferor Bank/ Institution	Name of Transferee Bank/ Institution	Date of Amalgamation	Merger Type
1	Punjab Co-operative Bank Ltd.	Oriental Bank of Commerce	April 8, 1997	PVB to PSB
2	Bareilly Corporation Bank Ltd.	Bank of Baroda	June 3, 1999	PVB to PVB
3	Times Bank Ltd.	HDFC Bank Ltd.	February 26, 2000	PVB to PVB
4	Bank of Madura Ltd.	ICICI Bank Ltd.	March 10, 2001	PVB to PVB
5	Benares State Bank Ltd.	Bank of Baroda	June 20, 2002	PVB to PSB
6	Nedungadi Bank Ltd.	Punjab National Bank	February 1, 2003	PVB to PSB
7	Global Trust Bank Ltd.	Oriental Bank of Commerce	August 14, 2004	PVB to PSB
8	Ganesh Bank of Kurundwad Ltd.	Federal Bank Ltd.	September 2, 2006	PVB to PVB
9	United Western Bank Ltd.	IDBI Ltd.	October 3, 2006	PVB to PSB
10	Bharat Overseas Bank Ltd.	Indian Overseas Bank	March 31, 2007	PVB to PVB
11	Sangli Bank Ltd.	ICICI Bank Ltd.	April 19, 2007	PVB to PVB
12	Centurion Bank of Punjab Ltd.	HDFC Bank Ltd.	May 23, 2008	PVB to PVB
13	State Bank of Saurashtra	State Bank of India	August 13, 2008	PSB to PSB
14	Bank of Rajasthan	ICICI Bank	August 12, 2010	PVB to PVB
15	State Bank of Indore	State Bank of India	August 26, 2010	PSB to PSB
16	ING Vysya Bank	Kotak Mahindra Bank	April 01, 2015	PVB to PVB
17	State Bank of Bikaner and Jaipur State Bank of Hyderabad State Bank of Mysore State Bank of Patiala State Bank of Travancore Bhartiya Mahila Bank	State Bank of India	April 01, 2017	PSB to PSB

Note: PSB: Public Sector Bank, PVB: Private Sector Bank
Source: STRBI, Various Issues.

Annex II: List of Bank M&As during 2019-2020

Sr. No.	Name of Transferor Bank/ Institution	Name of Transferee Bank/Institution	Official Announcement Date	Date of Amalgamation	Merger Type
1	Vijaya Bank Dena Bank	Bank of Baroda	January 02, 2019	April 01, 2019	PSB to PSB
2	Oriental Bank of Commerce United Bank of India	Punjab National Bank	August 30, 2019	April 01, 2020	PSB to PSB
3	Syndicate Bank	Canara Bank	August 30, 2019	April 01, 2020	PSB to PSB
4	Andhra Bank Corporation Bank	Union Bank of India	August 30, 2019	April 01, 2020	PSB to PSB
5	Allahabad Bank	Indian Bank	August 30, 2019	April 01, 2020	PSB to PSB

Note: The merger between Lakshmi Vilas Bank and DBS India Pvt. Ltd., being a M&A transaction between PVB to FB, was not considered for the study.
Source: STRBI, Various Issues.

Annex III: Definitions of Financial Ratios

a) Liquidity Ratios: Measures changes in banks' cash position

i) Loans to Assets = Net Loans and Advances/Total Assets

ii) Loans to Deposits = Net Loans and Advances/Total Deposits

b) Profitability Ratios[15]: Measures the overall performance of the bank

i) Return on Assets (ROA) = Net Profit after tax / Total Assets

ii) Return on Equity (ROE) = Net Profit after tax / Total Capital + Reserves and Surplus

iii) Net Interest Margin (NIM) = (Interest Earned – Interest Expended) 100*/ Total Assets

iv) Cost to Income = Non-Interest Expense* 100 /Net Operating Income

c) Operating Efficiency Ratios: Measures the ability of bank managers to reduce costs and thus approximates employee productivity.

i) Operating Expense to Operating Income = Non-Interest Expense/Non-Interest Income

ii) Operating Expense to Net Operating Income = Non-Interest Expense/Net Operating Income

iii) Operating Expense to Total Assets = Non-Interest Expense/Total Assets

d) Capital Adequacy: Measures the ability of banks to absorb potential losses while remaining solvent and meet regulatory standards

i) Capital to Assets = Total Capital/ Total Assets

ii) Loans to Capital = Net Loans and Advances/Total Capital

iii) Deposits to Capital = Total Deposits/ Total Capital

e) Asset Quality: Measures changes in a bank's loan quality and credit risk associated with the lending business

i) GNPA ratio = Gross Non-performing Assets (NPAs)/ Gross Loans & Advances

ii) NNPA ratio = Net NPAs[16]/ Net Loans & Advances

f) NPA Provisions: Measures the ability of banks to provision against loss-making assets and also to meet regulatory standards.

i) Provision Coverage Ratio (PCR) = Total NPA provisions/Gross NPAs

---

15 Total assets under profitability ratios are calculated as the average of current and previous year.

16 Net NPAs are calculated as Gross NPAs less NPA Provisions.

Annex IV: DEA Methodology

Let us assume there are n DMUs, p inputs and q outputs for each DMU. For i^{th} DMU, $x_i = (x_{1i}, x_{2i} \ldots\ldots x_{pi})$ be the $p\ x\ 1$ input vector and $y_i = (y_{1i}, y_{2i} \ldots\ldots y_{qi})$ be the $q\ x\ 1$ output vector. Let $X = (x_1, x_2 \ldots\ldots x_n)$ be the $p\ x\ n$ matrix of inputs and $Y = (y_1, y_2 \ldots\ldots y_n)$ be the $q\ x\ n$ matrix of outputs. For each DMU, a ratio of all outputs over inputs $\frac{u' y_i}{v' x_i}$ is computed where u is $q\ x\ 1$ vector of output weights and v is $p\ x\ 1$ vector of input weights. To obtain optimal weights under CRS, the following mathematical programming problem is being specified:

$$\max_{u,v} \left(\frac{u' y_i}{v' x_i}\right),$$

st[17] $\frac{u' y_j}{v' x_j} \leq 1;\ j = 1,2, \ldots\ldots, n$

$u, v \geq 0$

The above formulation has a problem of infinite number of solutions since the efficiency measure of the i^{th} DMU is maximized subject to the constraint that the efficiency measures of all remaining DMUs must be less than or equal to one. To counter this problem, the constraint $v' x_i = 1$ is imposed that leads to:

$max\ \mu'\ y_i\,,$

$st\ \varphi'^{x_i} = 1,$

$\mu'\ y_j - \varphi' x_j \leq 0;\ j = 1,2, \ldots\ldots, n$

$\mu, \varphi \geq 0$

Using duality in linear programming, an equivalent envelopment form can be derived as:

$$\min_{\theta,\lambda} \theta,$$

st $-y_i + Y\lambda \geq 0,$

$\theta x_i - X\lambda \geq 0,$

$\lambda \geq 0$

where, θ is a scalar that represents the value of the efficiency score of i^{th} DMU such that $0\ \leq \theta\ \leq 1$ with $\theta = 1$ indicating an efficient DMU lying on the frontier. Since λ is a vector of $n\ x\ 1$ constants, the above linear programming problem has to be solved n times to obtain the value of θ for each DMU in the sample.

---

17 st stands for "subject to".

The CRS assumption under DEA-CCR would be plausible if all banks (DMUs) in the sample are operating at their optimal scale, which is a very stringent condition. To avoid this problem, Banker, Charnes and Cooper (1984) extended the DEA-CCR model to allow for variable returns to scale. Accordingly, the CRS linear programming specification in the above equation is modified by adding the convexity constraint $NI'\lambda = 1$:

$\min_{\theta,\lambda} \theta$,

st $-y_i + Y\lambda \geq 0$,

$\theta x_i - X\lambda \geq 0$,

$NI'\lambda = 1$,

$\lambda \geq 0$

where, NI is a $N\ x\ 1$ vector of ones.

Reserve Bank of India Occasional Papers

Vol. 43, No. 1: 2022

Behaviour of Credit, Investment and Business Cycles: The Indian Experience

Sujeesh Kumar, Pawan Kumar and Anand Prakash*

Received on: January 18, 2022
Accepted on: June 17, 2022

This paper examines the nature and degree of causal relationship between credit, investment and business cycles in India during the period 1950-51 to 2020-21. The duration of cycles and their turning points have been estimated using the National Bureau of Economic Research (NBER) dating procedure. The phase synchronisation of cycles is assessed using a concordance index. The paper finds that the credit, investment and business cycles interact with each other and have bi-directional causal linkages. The results also indicate an increase in phase synchronisation of the Indian credit cycle with that of the emerging market economies (EMEs) and advanced economies (AEs) after the global financial crisis.

JEL Classification: C22, E32, E58, D91

Keywords: Credit cycle, business cycle, investment cycle, synchronisation, concordance index, non-bank sources

* Sujeesh Kumar S. (sujeeshks@rbi.org.in) is Assistant Adviser, Pawan Kumar (pawankumar2@rbi.org.in) is Manager and Anand Prakash (aprakash@rbi.org.in) is Director in Monetary Policy Department, Reserve Bank of India (RBI). The views expressed in the article are those of the authors and not of the RBI. The authors are thankful to Jessica Antony for her insightful comments on an earlier version of the paper. Authors would also express their sincere gratitude to the participants of the DEPR Study Circle at RBI, Mumbai, for offering suggestions and comments to improve the quality of this paper. We are also thankful to Priyanka Upreti for her editorial support and an anonymous reviewer for valuable comments.

Introduction

Studies on the cyclical patterns of macroeconomic variables are not new, and the cyclical pattern analysis indeed has its own history (Tinbergen, 1939; Schumpeter, 1954; Lee, 1955). A significant development in the field of economic cycles was the identification of cycles and their phases, such as expansion, crisis, recession and recovery (Kitchin,1923; Schumpeter, 1954; Lee,1955). Although this was the initial work, the focus of cyclical pattern analysis even now is centered on these aspects.

There have been instances where the economic cycles have been named after the inventors, such as the 'Juglar cycle' for fixed investment and the 'Kuznets swing' for infrastructure investment, among others (Korotayev *et al.*, 2010). The cyclical patterns of key macroeconomic variables and their behaviour have fascinated researchers, and as a result, various theories around these cycles have been propounded in the literature.

Historically, the emphasis was given on the business cycle as it dealt with the growth aspects of an economy. The business cycles were extensively studied across the globe, including in the Indian context. However, after the global financial crisis (GFC) in 2008, the focus has shifted towards financial cycles, notwithstanding the continued importance of the business cycle analysis. The GFC has kindled greater interest among economists in the cyclical behaviour of financial variables. This aspect has also engaged the attention of researchers and policymakers, including central bankers, all over the world. The recent literature suggests that financial cycles duration is larger than that of business cycles. This pattern has been witnessed across the globe, especially after the GFC (Claessens *et al.*, 2011, 2012; Drehmann *et al.*, 2012; Strohsal, 2015; Pontines, 2017; Borio *et al.*, 2018). The financial cycle analysis generally involves financial variables, such as bank credit, housing prices, non-bank credit, equity prices, *etc.*

The literature on financial cycles for the developed markets is vast. However, the studies for the emerging market economies (EMEs) are relatively few, specifically in the Indian context. The literature for India shows that business cycles have got elongated after the introduction of economic reforms during 1990-91. In the Indian context, there are a few studies on the business cycles as well (Mall, 1999; Mohanty *et al.*, 2003; Dua and Banerji, 2006; Dua and Banerji, 2012; Ghate *et al.*, 2013; Pandey *et al.*, 2017). Some studies in the Indian context have also examined the duration of the investment cycle. The investment cycle should ideally be aligned with the business cycle, as investment and GDP growth are closely related. A recent study has suggested that investment cycles in India have an average duration of three years (Raj *et al.*, 2018).

A study on the financial cycle in the Indian context was first attempted by Behera and Sharma (2019), which concluded that the financial cycle has a longer duration than that of the business cycle. Specifically, they found that the average duration of business cycles in India was about five years and that of the credit cycle about 15 years in the post-reforms period.

The financial cycle analysis focuses on the aggregate effect of all financial variables on the real economic variables. Even though credit is one of the main components of a financial cycle, a separate and detailed analysis of credit cycles is not available in the Indian context. Credit cycle is not only crucial in connection with the financial cycle analysis but also for the study of financial stability. As a result, credit cycles have engaged the attention of central bankers, given their mandate of financial stability.

Credit is also associated with the business and investment cycles. The co-movement between credit and business cycles reflects the relationship between financial and real sectors of the economy. Financial frictions can amplify credit cycles, resulting in their longer durations and amplitudes. Several studies have argued that financial development beyond a threshold level may inhibit growth, specifically excess credit growth may cause reversal of the economic growth process (Cecchetti and Kharroubi, 2012; Law and Singh, 2014; Rath and Kumar, 2021). Therefore, studying credit booms and credit crunches is important, especially after the GFC.

Generally, economists analyse the boom and bust phases of an economy through cycles of various macroeconomic variables, such as output, investment, consumption and credit. The term 'economic cycle' refers to economy-wide fluctuations, that occur around a long-term growth trend, in production or economic activity over several months or years. Besides, these fluctuations involve alternate shifts over time between periods of relatively rapid economic growth (expansion or boom), and periods of stagnation or decline in growth (recession or depression) (Sullivan and Sheffrin, 2006). The cyclical patterns or fluctuations can be visible over longer periods of time for any macroeconomic variables. In the conventional cyclical analysis, cycles of macroeconomic variables, such as credit, investment and GDP are estimated using long time-series data and applying a suitable extraction methodology. These cycles interact with each other as the macroeconomic variables are closely inter-related.

In the financial systems, funds are raised from either banks or non-bank sources. The non-bank sources of finance are generally heterogeneous and include private placements of debt instruments, public offerings or loans from a varied group of lenders like investment funds, external borrowings from foreign lenders, *etc.* The non-bank credit in AEs is relatively larger than EMEs. However, the dependence on non-bank sources has been growing even in EMEs in the recent years, with non-bank sources increasingly complementing bank credit.

The synchronisation of the bank credit cycle and non–bank credit cycle is not uniform and can vary from country to country or can change due to financial shocks in the economy. Studies have also shown that excessive growth of bank credit is a leading indicator of systemic banking crises. Non-bank credit cycle can act as a leading indicator of currency crises or sovereign debt crises (Kemp *et al.*, 2018). Yet, given the growing importance of non-bank funds, it is important to assess the association between bank credit and non-bank funding cycles.

Against this backdrop, this study examines the behaviour of the credit cycle, both bank credit and non-bank funds, investment cycle, and business cycle in India during the period 1950-51 to 2020-21. The study analyses the phase synchronisation between credit, investment and business cycles. This study also analyses the synchronisation between credit cycle of India with that in EMEs and AEs.

The remaining part of the paper is structured as follows: Section II presents a brief review of literature. Section III presents the stylised facts and Section IV discusses the key non-bank sources of finance in India. Section V discusses the methodology and data used in this paper. Section VI explains the empirical findings, while section VII presents the concluding remarks.

Section II
Review of Literature

Finance was generally viewed as a sideshow to macroeconomic fluctuations as part of the pre-GFC paradigms, but this view was proved wrong during the GFC (Drehmann *et al.*, 2012). After the GFC, there has been an increased interest in studying the relationship between real and financial variables. Traditionally, studies about business cycles have focused on the behaviour of real macroeconomic variables. Cycles of financial variables attained importance particularly after the GFC. Furthermore, longer durations of financial cycles were observed after the GFC. The idea of a long financial swing was initially discussed by Minsky (1964).

Credit plays a prominent role in the financial development of any economy. The credit cycle is distinct from the business cycle in its frequency and amplitude (Aikman *et al.*, 2015; Drehmann *et al.*, 2012). Credit cycle has the predictive ability, as it can act as a leading or a lagging indicator of economic growth. Some studies assert that credit is a lagging indicator (Haavio, 2012; Haavio *et al.*, 2013; Runstler and Vlekke, 2017), while others claim it to be a leading indicator (Gomez-Gonzales *et al.*, 2014) of business cycles.

In addition to the credit cycle, recent studies have also dealt with the financial cycle, with credit as one of its key components. For the construction of a financial cycle, researchers have typically considered variables such as bank credit, other forms of credit, housing prices, *etc.*

The financial cycle is used to analyse financial stability by central banks. Borio *et al.* (2018) studied financial cycles extensively and their implications for the economy, particularly in connection with the GFC.

Empirical research suggests that financial cycles have a longer duration and shorter frequency than the business cycle (Claessens *et al.*, 2011, 2012; Drehmann *et al.*, 2012; Strohsal, 2015; Pontines, V., 2017; Borio *et al.*, 2018). Based on a large country sample covering 40 years, Borio *et al.* (2018) noted that credit booms undermine growth, as they result in the misallocation of resources to a sector with lower productivity growth, and the subsequent impact will be larger if the boom is followed by a banking crisis.

Hieberta *et al.* (2018) empirically examined the characteristics of financial and business cycles of 13 European Union countries. They found that financial cycles have a longer duration and greater symmetry than business cycles. Moreover, among the 13 countries, those which experienced severe financial downturns exhibited a weaker similarity in the patterns of their cycles. This showed that financial cycles cannot be similar for countries that have experienced financial crises. Alternatively, the crises could be impacting financial cycles differently depending on their severity and the individual country's economic scenario and policy actions.

Runstler and Vlekke (2017) studied the cyclical components in GDP, credit volumes, and house prices for the US and the five largest European economies. Their estimates suggested that large and long cycles of credit and house prices were correlated with a medium-term component in GDP cycles.

Credit can also be raised from non-bank sources. Oftentimes, a non-bank form of credit is a substitute for bank credit if the bank credit is costlier or not easily available for the investors (Kemp *et al.*, 2018). IMF (2015) refers to market-based financing as a 'spare tyre' during the periods of constrained bank credit. The literature suggests that a large reliance on non-bank debt or market-based finance, relative to bank credit, can facilitate economic growth and financial stability (Gambacorta *et al.*, 2014; Bats and Houben, 2017). On the other hand, there are several examples of stress events in the non-bank sector, and some of which have been systemic in nature (ESRB, 2016).

The main focus of credit cycle analysis is to explain either the economic growth or financial stability. There are a few studies that connect credit cycle to the monetary policy as well. According to the findings of Brauning and Ivashina (2019), during the monetary policy easing cycles in the US, the volume of loans sanctioned by foreign banks increased significantly in the EMEs. This was followed by credit contraction when the monetary policy was tightened by the US. Thus, the US monetary policy influenced credit cycles in EMEs, as the availability of foreign bank credit to EMEs is closely related to the US monetary policy.

Credit growth facilitates investment and economic growth, and higher economic growth in turn leads to more demand for investment and credit. Thus, credit has causal relationships with both investment and GDP. As noted by Kent and D'Arcy (2001), the strength of economic activity determines credit demand, and the financial system's health influences credit supply, which in turn affects the economic activity.

Episodes of rapid credit growth (*i.e.*, credit booms) have also been associated with periods of economic distress owing to overheating of the economy (Mendoza and Terrones, 2008). Therefore, excessive credit growth is one of the critical early warning indicators of macroeconomic and financial instability in an economy.

Credit cycles may often develop as a result of the business cycle, as banks' lending typically accelerates during a period of economic expansion and weakens during a contraction phase. From the supply side, during economic booms, business optimism and rising collateral values[1] lead bankers to expand lending even at the cost of loosening lending standards. By contrast, during downturns, a pessimistic outlook results in deferred lending decisions (Samantaraya, 2007 and Ariccia *et al.*, 2012).

From the demand side, inherent optimism (pessimism) about economic activity, connected with the business cycle, expands (restricts) investment and consumption spending in response to higher (weaker) expected income, wealth, and effective demand, influencing credit demand.

Additionally, during the expansionary phases, abundant credit supply leads to higher investment and consumption, and enhanced collateral values. The process is reversed during a downturn. This implies that the nature of bank credit is typically procyclical (IMF, 2008). Banerjee (2011) also noted the procyclical nature of credit in the Indian context. Procyclicality of the financial system generally refers to the mutually reinforcing interactions ('positive feedback') between the real and financial sectors of the economy that amplify the business cycle and are usually the source of financial instability (Drehmann *et al*., 2011). This procyclicality of credit has been a major driver of the increase in the amplitudes of business cycles, in effect, exacerbating the economic cycles (Banerjee, 2011). Therefore, it is vital to

---

1 Typically, excessive credit (growth) accelerates increase in property and asset prices, which, in turn, inflates collateral values and, therefore, the amount of credit the economic agents can gain until, at some point, the process gets reversed (Borio *et al*., 2019).

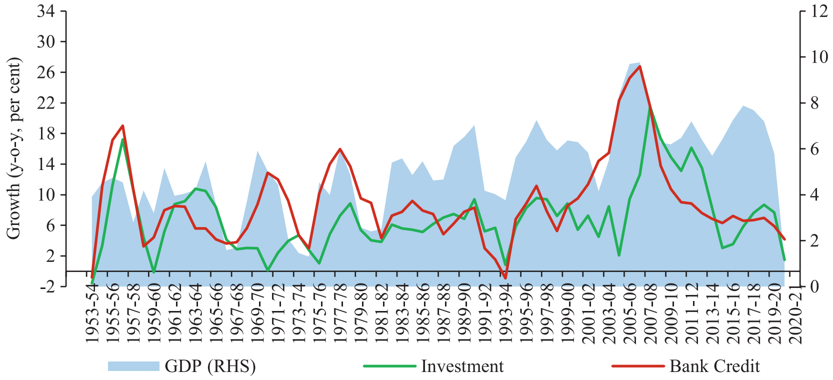
understand the cyclical characteristics of credit and its relationship with other major macroeconomic variables, while formulating early warning indicators of macroeconomic imbalances and devising policy response to business cycles.

Section III
Stylised Facts

III.1. Characteristics of Credit, Investment and Business Cycles in India

As noted earlier, the relation between real and financial sectors have attracted greater attention of researchers and policymakers after the GFC. In a strong bank-based economy like India, bank credit is a major source of finance. Bank credit has also supported infrastructure financing in recent decades. The investments in physical assets get reflected in the gross fixed capital formation (GFCF), which is one of the major components of GDP. The 3-year moving averages of GDP, investment, and bank credit growth rates (y-o-y) are presented in Chart 1, which shows that acceleration or deceleration in growth rates of these three variables are closely associated with each other. Bank credit growth, which touched its peak in 2006-07, has witnessed a downtrend since the GFC, which coincided with a slowdown in investment and economic growth.

Chart 1: Bank Credit, Investment, and GDP



Note: (i) Data from the period 1950-51 to 2020-21.
(ii) Credit is the total non-food bank credit extended by all scheduled commercial banks in India.
(iii) Gross fixed capital formation, which is a proxy for the total investment.
(iv) Real GDP is based on the base year 2011-12.

Sources: Reserve Bank of India and National Accounts Statistics, Government of India.

Table 1: Summary of Key Growth Statistics

Periods	Growth (per cent)			Volatility		
	Bank Credit	Invest-ment	GDP	Bank Credit	Invest-ment	GDP
1950-51 to 1979-80	7.9	4.9	3.6	8.3	7.0	3.3
1980-81 to 1989-90	7.6	6.2	5.6	2.9	1.8	1.9
1990-91 to 2007-08	11.9	8.0	6.4	10.0	8.7	2.7
2008-09 to 2020-21	6.5	6.8	5.5	2.7	7.4	4.1

Note: GDP, investment, and credit growth are in real terms. Volatility measured by the standard deviation.
Sources: Reserve Bank of India and National Accounts Statistics, Government of India.

Some of the key growth statistics of the Indian economy over different time periods are given in Table 1. The period between 1950-51 to 2020-21 is split into four sub-periods: 1950-51 to 1979-80, 1980-81 to 1989-90, 1990-91 to 2007-08 and 2008-09 to 2020-21.

During the first three decades after independence (1950-51 to 1979-80), the annual average economic growth rate was the lowest at around 3.6 per cent. During this period, average growth rates of investment and credit were 4.9 per cent and 7.9 per cent, respectively. However, the Indian economy experienced a turnaround in the 1980s, with a slow shift towards liberalisation, as GDP and investment growth rate picked up significantly, even though credit growth softened marginally. In the 1990s, the initiation of economic reforms in the early 1990s brought about structural changes in the economy. Though, credit growth decelerated somewhat in the 1990s, it subsequently recovered sharply, registering a double-digit growth from the beginning of the 2000s that continued till the advent of the GFC in 2007-08. GDP and investment growth registered an increase during the period 1990-91 to 2007-08. However, during 2008-09 to 2020-21, the average growth of all the above-mentioned macro variables moderated significantly.

The pace of credit growth, which was 2.2 times and 1.6 times that of GDP and investment growth, respectively, during 1950-51 to 1979-80, moderated to 1.4 times and 1.2 times during 1980-81 to 1989-90. During the period 1990-91 to 2007-08, credit growth was 1.9 times and 1.5 times that of GDP and investment growth, respectively. However, the volatility of GDP, investment, and credit growth, which was relatively low during the 1980s, increased significantly in this phase. In the post-GFC period, during 2008-09 to 2020-21, credit growth reduced noticeably. In this period, volatility in investment and credit growth rates moderated, though volatility in GDP growth increased.

Section IV
Sources of Non-Bank Finance in India

Even though the financial requirements of the Indian economy are primarily met by the banking sector, alternative non-banking sources are increasingly being used for financing investment projects. For instance, the Indian corporate sector relies on external commercial borrowings (ECBs) and funds mobilised from the capital markets, mainly equities and private placements of bonds. Moreover, new avenues, such as venture capital funds, private equity funds, and angel funds are being used, particularly by start-ups.

Research on alternative investments in EMEs is at a nascent stage but is growing rapidly (Cumming and Zhang, 2016). In this study, for the construction of the non-bank[2] funding cycle, aggregate value of three sources of non-bank finance *viz*., (a) external commercial borrowings (ECBs), (b) resources mobilised from capital markets, and (c) foreign direct investment (FDI) have been used.

IV.1 External Commercial Borrowings

The borrowing behaviour of Indian corporates is broadly driven by the investment demand, which, in turn, is a function of expected economic growth in the future. The investment demand can be financed through external funds or internal funds. ECBs are one of the sources for meeting such fund requirements and have emerged as a significant source of the flow of funds in India (Chart 2a). A firm's preference between borrowings from the domestic

---

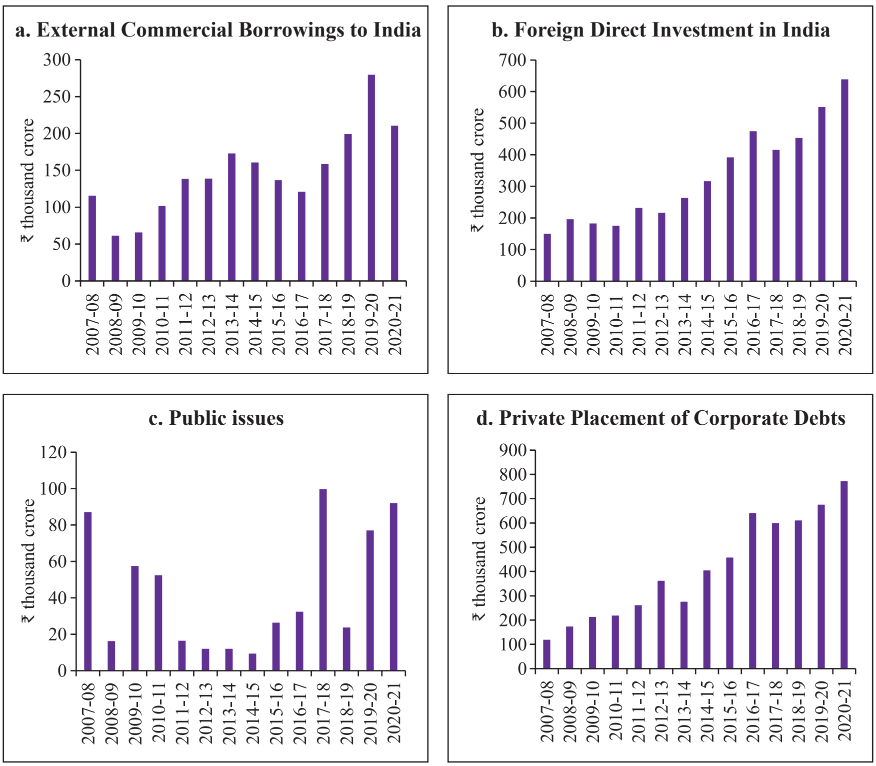
[2] Non-bank generally refers to non-banking financial companies (NBFCs). However, in this study, for arriving at non-bank funds, three sources have been used *viz.*, resources mobilised from the markets, external commercial borrowings and foreign direct investment. Credit extended by NBFCs has not been separately included in non-bank funds, as NBFCs generally source their funds from banking sector, from financial markets and also through external commercial borrowings. Taking credit extended by NBFCs separately to arrive at non-bank funds may result in double counting. Additionally, time series data for credit extended by NBFCs for a sufficiently long time period is not readily available.

capital market or the overseas markets is typically made after a thorough long-term financial planning (World Bank, 2007).

IV.2 Foreign Direct Investment in India

Following liberalisation in 1991 and the subsequent amendment of the new industrial policy (NIP) coupled with integration of the Indian economy with the world economy, the industrial policy regime has changed significantly. The policy reforms have enhanced the attractiveness of India as a long-term investment destination resulting in a significant increase in FDI flows. Foreign investors come to India also for its locational advantages, relaxed entry norms, and growing interest in the country's services and manufacturing sector. Consequently, FDI inflows into India have increased significantly over the last decade (Chart 2b).

Chart 2: Alternate Sources of Finance for Investment



Note: i. Public issue includes IPO, FPO and Rights issues,
ii. Private placement includes debt and equity.

Sources: Reserve Bank of India and Securities and Exchange Board of India.

IV.3 Resources Mobilised through Primary Markets

Resource mobilisation through primary markets covers the Initial Public Offerings (IPOs) and private placements. The quantum of private placements has witnessed a significant increase in recent years over public issues (Charts 2c and 2d).

Section V
Methodology and Data

Representing an economic or financial time series variable by Y_t, a cycle y_t can be defined as a pattern seen in the series. Burns & Mitchell (1946) have defined business cycle as a type of fluctuation in the aggregate economic activity of nations. Thus, the cyclical characteristics of cycle y_t are extracted from the corresponding time series data of variable Y_t. The nature of y_t is generally described with parametric statistic models that would effectively describe the temporal behaviour of y_t.

In the cyclical analysis, the first step is to extract the cyclical component of the time series Y_t, after adjusting the seasonal fluctuations in Y_t, using a suitable methodology. There are three common approaches to estimate cycles. The classical approach[3], the growth cycle approach, and the growth rate approach. In the Indian context, especially in the post-reforms period, the most suitable approach is the growth cycle or growth rate cycle approach, as the classical approach is not useful in identifying the turning points (Patnaik and Sharma, 2002; Mohanty *et al.*, 2003; Dua and Banerji, 2012; Pandey *et al.*, 2017). Following Pandey *et al.* (2017), the growth cycle approach has been used for the estimation of cycles in this paper.

Further, the estimation of any cycle is accomplished by identifying the turning points in y_t, *i.e.*, peaks and troughs. The turning point dates mark the beginning of expansion and contraction phases of an extracted cycle y_t. There are various filters commonly used for extracting cyclical components of a time

---

[3] Classical approach is based on the level series with no adjustment for long term trend. Growth cycles are measured through fluctuations in the deviations of the key indicators around their long-run trends and require trend estimation and elimination (Zarnowitz and Ozylidirim, 2002). In the growth rate cycle approach, the growth rate of variable is considered for the extraction of cycles.

series. Each one has its own advantages and disadvantages depending upon the algorithms used. Popular among them are Hodrick - Prescott (HP) filter, Band-Pass (BP) Filter, Hamilton filter, and Christiano – Fitzgerald (CF) filter (Christiano and Fitzgerald, 2003).

One of the limitations of the HP filter is that the cycle estimated using HP filter is sensitive to different values of the smoothing parameter (Bjornland, 2000). The choice of the smoothing parameter (λ) in the HP filter has implications for the variability of the trend term. Further, it can yield spurious relations that are unrelated to the underlying data-generating process (Hamilton, 2016). Therefore, alternate filters have been used in the literature for extracting the cyclical components.

One of most effective filters is the CF filter, which has been used in this paper. This filter is time-invariant and works based on the power spectrum of the time series. It does not change the relation between time series components at any frequency. These are the advantages of the CF filter over other filters, such as the HP filter or BP filter.

Bry and Boschan (1971) first gave the dating algorithm (BB) for the estimation of turning points, which is based on the cyclical components extracted from the time series. This extraction technique can be applied to a monthly or quarterly data series. The quarterly version of the BB algorithm can also be combined with some censoring rules, sometimes called Bry and Boschan Quarterly (BBQ)[4] algorithm. A popular dating procedure is the NBER procedure, which is based on the BB algorithm. This study uses the NEBR dating procedure to obtain the turning points, durations, and amplitude of the cycles.

Conventionally, business cycle analysis deals with a period of 2-8 years, referred to as short cycles in the business cycle literature and cycles covering a period beyond eight years are generally referred to as medium cycles. In this paper, both short cycles and medium cycles of all variables have been estimated for a better understanding of the behaviour of the cycles and the relationship between them.

---

4 Alternate approaches for dating have also been developed using dynamic factor models or probabilistic approach (Hamilton, 1989; Chauvet, 1998; Chauvet and Hamilton, 2006).

The phase synchronisation between the various cycles can be statistically measured using a concordance index. It calculates the average number of periods in which two variables coincide at the same phase of a cycle. As the index construction is based on gaps, two components of the series, *viz*., a long-term trend component and a cyclical component are needed for each variable. If x_t and y_t are the two series of interest with the long-term trend of both these series being represented by $\bar{x}_t$ and $\bar{y}_t$, respectively, the gap is measured as the deviation from the long-term trend levels, say $\hat{x} = x_t - \bar{x}_t$ and $\hat{y} = y_t - \bar{y}_t$. In order to study the synchronisation between cycles, phases of the cycles are mapped into binary variables as follows:

$$B_{i,j}^{y} = \begin{cases} 1 \;\; if\ \hat{y}_{i,j} > 0 \\ -1\ if\ \hat{y}_{i,j} < 0 \end{cases} \qquad B_{i,j}^{x} = \begin{cases} 1 \;\; if\ \hat{x}_{i,j} > 0 \\ -1\ if\ \hat{x}_{i,j} < 0 \end{cases} \qquad \text{...(1)}$$

and

$$S_{i,j}^{y} = \begin{cases} 1 \;\; if\ \hat{y}_{i,j} - \hat{y}_{i,j-1} > 0 \\ 0\ if\ \hat{y}_{i,j} - \hat{y}_{i,j-1} < 0 \end{cases} \quad S_{i,j}^{x} = \begin{cases} 1 \;\; if\ \hat{x}_{i,j} - \hat{x}_{i,j-1} > 0 \\ 0\ if\ \hat{x}_{i,j} - \hat{x}_{i,j-1} < 0 \end{cases} \qquad \text{...(2)}$$

Using the above equations (1) and (2), a measure of the degree of synchronisation between the cycles, called the concordance index (CI), proposed by Harding and Pagan (2002) is calculated as follows:

$$CI = \frac{1}{T}\left[\sum_{i=1}^{T} S_{it}^{y} S_{it}^{x} + \sum_{i=1}^{T}(1 - S_{it}^{y})(1 - S_{it}^{x})\right] \qquad \text{...(3)}$$

$$0 \leq CI \leq 1$$

CI indicates the number of periods for which the two cycles are in same phase and averages them out over *T* periods. The values of *CI* can range from zero to one with zero indicating perfect misalignment between phases of two series considered and one implying perfect alignment.

Various steps are involved starting from the estimation of the cycle to the calculation of the concordance index as follows:

i) First, we seasonally adjust the quarterly data series for seasonal fluctuations. In India, the official statistics do not feature seasonal adjustment. Therefore, the series is seasonally adjusted using the X-14-ARIMA method.

ii) In the second step, the cyclical component of each series is extracted from the seasonally adjusted log transferred series using Christiano-Fitzgerald asymmetric filter.

iii) Next, the turning points and durations of the cycles are estimated using the NEBR dating procedure. The details of the NEBR procedure and CF Filter are given in the Annex A1 and A2.

iv) Finally, the phase synchronisation between various cycles is estimated using a concordance index.

The four key variables used in the paper are bank credit, non-bank funds, investment, and GDP. Bank credit is the total non-food credit extended by all scheduled commercial banks in India. Non-bank funds refer to alternative sources of funding for the Indian corporates, such as external commercial borrowings (ECBs), resources mobilised from primary markets, which include public offerings and private placements, and foreign direct investment (FDI).

To estimate the business cycle, total output of the country measured by real GDP has been used. The gross fixed capital formation, which is a proxy for the total investment, has been used to derive the investment cycle. Annual time-series data have been used for extracting GDP, investment, and bank credit cycles. However, non-bank funding cycle has been derived from quarterly data, as annual data are not unavailable over a longer period. Quarterly GDP, investment, and bank credit data have also been used to estimate cycles in order to compare their synchronisation with the non-bank funding cycle.

All variables are in real terms and quarterly data are seasonally adjusted using the X-14-ARIMA method before estimating the cycles. Annual series are for the period 1950-51 to 2020-21, while quarterly series are for the period quarter ending June 1997 (1997-98: Q1) to the quarter ending March 2020 (2019-20: Q4). The details of each variable and their sources along with descriptive statistics are given in Annex Tables A3 and A4.

Section VI
Empirical Analysis

VI.1. Cycles and Turning Points

The severity of the depression phase of a cycle or the strength of its expansionary phase is measured by the duration and amplitude of the cycle. Duration measures the length of a cycle, whereas amplitude measures the degree of change in the cyclical phase. A downturn's duration can be computed by calculating the number of years/quarters between a peak and a trough, while an upturn's duration can be determined by counting the years/quarters that pass from trough to peak. The amplitude for the downturn is computed based on the deceleration in each respective variable from the peak to the next trough, while the same for the upturn measures the change in a variable from trough to peak.

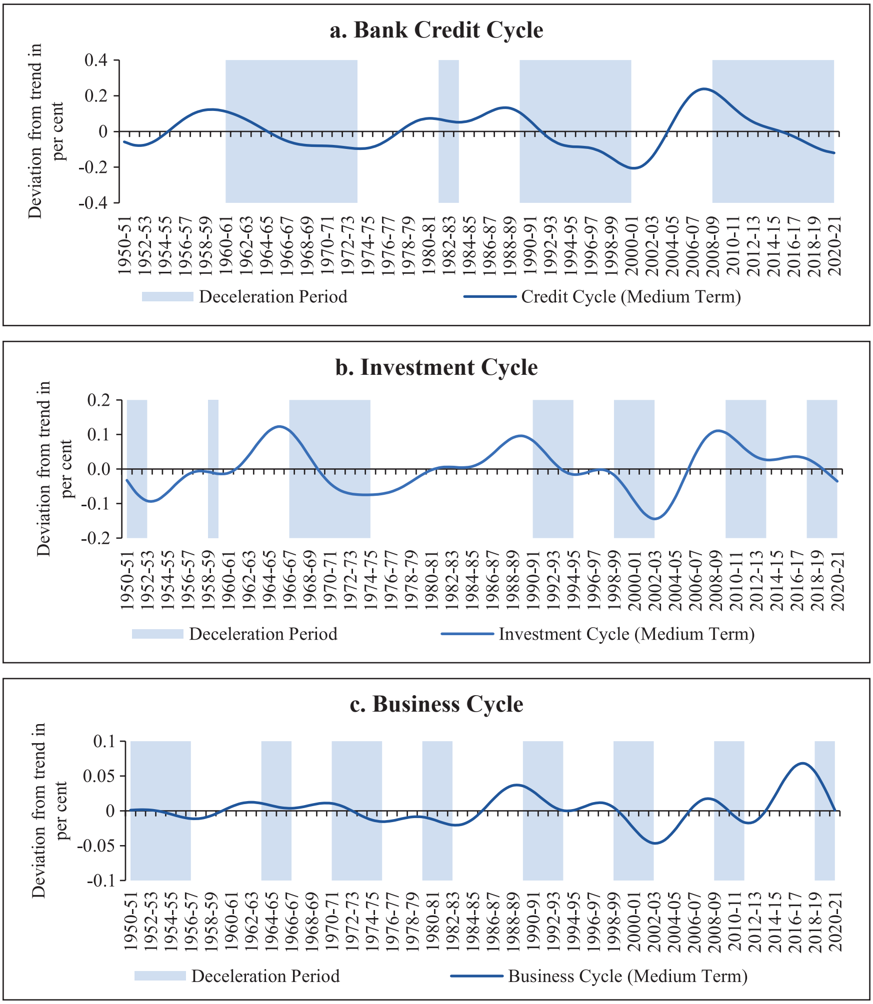
The cyclical components of bank credit, investment and GDP for the period 1950-51 to 2020-21 have been extracted using the CF filter and turning points are identified by the NEBR dating procedure. The credit cycle, investment cycle and the business cycle (GDP cycle) have been plotted in Chart 3. The cycle turning points have been analysed with reference to the reforms period in India, as macro analysis typically compares post-reforms and pre-reforms periods (Ghate *et al.*, 2013; Banerjee, 2011; Behera and Sharma, 2019). Accordingly, the business, investment and credit cycles have been separately analysed for two periods – from 1950-51 to 1990-91 (the pre-reforms period) and from 1991-92 to 2020-21 (the post-reforms period).

The basic cyclical characteristics of these macroeconomic variables are given in Table 2. As indicated earlier, the descriptive statistics of the cyclical characteristics are also given for pre- and post-reforms periods. Volatility measured by the standard deviation of each cyclical series is similar across short cycles, while medium cycles of GDP and credit exhibit higher volatility in the post-reforms period as compared to the pre-reforms period. However, the investment cycle exhibited lower volatility in the post-reforms period. The relative volatility[5] of medium duration credit cycle was higher than that of an investment cycle during both the pre- and post-reforms period, while it was smaller for the short cycle in the post-reforms period. In general, the contemporaneous correlations of both credit and investment cycles with the GDP cycle increased during the post-reforms period.

---

5 Relative volatility is estimated by taking the ratio of the standard deviations of the cycle of the variable of interest to the standard deviation of the reference cycle, which is GDP representing the aggregate economic activity. A higher relative volatility value (greater than unity) indicates that the cyclical amplitude of the variable is greater than that of the aggregate business cycle.

Chart 3: Credit, Investment, and Business Cycles



Note (i) Data is for the period 1950-51 to 2020-21.
(ii) Credit is the total non-food bank credit extended by all scheduled commercial banks in India.
(iii) Investment is proxied by gross fixed capital formation.
(iv) Cyclical component is extracted using CF filter following growth cycle approach.

Sources: Reserve Bank of India and National Accounts Statistics, Government of India.

VI.2. Durations of Cycles

Estimates of the duration of expansionary and contractionary phases of the Indian business cycles are presented in Table 3. According to our analysis based on short cycles, the duration of both the investment and business cycles is eight years, while the duration of the credit cycle is seven years. Considering

Table 2: Cycle Statistics for the Indian Economy Based on Annual Data

	Pre-reforms (1980-81 to 1989-90)				Post-reforms (1990-1991 to 2020-21)			
	Mean	Volatility	Relative Volatility	Correlation	Mean	Volatility	Relative Volatility	Correlation
Short Cycle								
GDP	-0.0002	0.02	1	1	0.0002	0.02	1	1
Investment	-0.0002	0.04	1.96	0.32	0.0015	0.04	2.15	0.80
Credit	-0.0005	0.05	2.39	0.50	0.0006	0.03	1.51	0.57
Medium Cycle								
GDP	0.0004	0.01	1	1	0.0055	0.03	1	1
Investment	-0.0027	0.06	4.45	0.54	-0.0013	0.04	1.41	0.60
Credit	0.0142	0.08	5.75	0.19	-0.0127	0.13	4.42	0.13

Note: (i) Volatility is measured as the standard deviation of the variable of interest and it gives the aggregate fluctuations of the variable.
(ii) Correlation is the simple Pearson correlation between the variables and GDP.
Source: Authors' estimates.

medium cycles, the average duration of the credit cycle in both expansion and contraction phases is longer than that of the business cycle. The average duration of the credit cycle is 17 years, while that of the business cycle is nine years. The duration of the expansion phase of the credit cycle varied from 5 to 10 years, while the duration of the contraction phase varies from 3 to 14 years (Annex Tables A5 and A6). The presence of large credit cycles was observed after the initiation of financial sector reforms in India. Behera and Sharma (2019) also noted the presence of medium-term financial cycles in India in the post-reforms period.

The average duration of the credit cycle tended to be longer than the duration of the business cycle, as any deterioration in corporate fundamentals or asset prices takes time to manifest and financial vulnerabilities reduce over a long-time horizon as balance sheet repair is a protracted process, thereby leading to an elongation of the duration of credit cycle. The difference in length of the cycles means that the span of one credit cycle is longer than one business cycle. This implies that even when business activities slow down, there may be a chance of over-extension of credit leading to the build-up of asset price bubbles. The reverse may happen when economic activities start picking up but a pickup in credit offtake may be delayed. Thus, there may be leads and lags resulting in a credit cycle duration being longer than that of a business cycle. Any failure to recognise the longer duration of credit cycle may result in greater economic disruption, especially when the asset price bubble created by excessive credit extension bursts.

During periods of uncertainty, there could be time and cost overruns, which may extend the length of the credit cycle, as banks may continue to lend, even at a slower pace, due to the effect of monetary or macro-prudential policies used by the authorities to address the situation. Similarly, the duration of expansionary and contractionary phases of a credit cycle is not expected to be symmetric over time; various macro-economic, financial, and other shocks may prolong/shorten the duration of a phase of a cycle.

The duration of the business cycle varies in the range of 3 to 6 years and 3 to 7 years in the expansionary and contractionary phases, respectively. It is observed that the contractionary phase of the credit cycle is more prolonged than the expansionary phase. The average duration of contractionary phase of the credit cycle is around 11 years, which is higher than the average duration of around seven years in the case of an expansionary phase.

The prolonged contractionary phase of the credit cycle witnessed in the post-GFC period may be viewed in the context of subdued bank credit demand, especially by the corporate sector, twin balance sheet[6] problem faced

Table 3: Average Durations of Credit, Investment, and Business Cycles

Durations	Bank Credit Cycle	Investment Cycle	Business Cycle
Short Cycle			
Expansion phase	4	3	4
Contraction phase	3	6	5
Full Cycle	7	8	8
Medium Cycle			
Expansion phase	7	6	5
Contraction phase	11	5	5
Full cycle	17	11	9

Note: Cyclical components are extracted using CF filter following the growth cycle approach. Durations and amplitudes are estimated using the NEBR dating procedure.
Source: Authors' estimates.

6 According to Economic Survey 2015-16, one of the challenges facing the Indian economy was the problem of the Twin Balance Sheet. Since balance sheets of both public-sector banks and corporate sector are linked, inability on the part of corporates to pay their debt to the banks affects the balance sheet of the banks as well.

by Indian banks and corporates, cleaning up of balance sheets by corporates and risk aversion on the part of banks. Besides, in the recent years, overall credit growth decelerated largely because of a slowdown in credit growth to the industrial sector owing to deleveraging by non-financial firms, increasing dependence of large corporates on non-bank sources of finance such as equity, bonds, and debentures (Kumar *et al.*, 2021).

The investment cycle also has a longer duration than that of the business cycle. In the expansionary phase, the duration varies from 3 to 15 years, while in the contractionary phase, it varies from 2 to 9 years. The average duration of a medium investment cycle in the expansionary and contractionary phases is around six years and five years, respectively.

Two major downturns in the investment and credit cycles, and three downturns in the business cycle can be seen in the post-liberalisation period. During the early 1990s, the Indian economy was hit by the balance of payments crisis, which was dealt with through a series of economic reforms initiated in 1991. In the first half of the 1990s, the Indian economy experienced a recovery in GDP growth. This, however, could not be sustained, and the growth declined noticeably in the second half of the 1990s. The loss of growth momentum in the second half was on account of the onset of the East-Asian crisis, a setback in the fiscal correction process, a slowdown in agricultural growth primarily due to poor monsoons, and deceleration in the pace of structural reforms. The slowdown in the growth rate could also be attributed to the investment boom during the earlier years of 1990s that had built large capacities (Acharya, 2002). Besides, as noted by Mohanty *et al.* (2003), muted demand for bank credit and investment coupled with slowing pace of currency expansion and import of capital goods were also witnessed in the second half of 1990s.

Coming to the 2000s, the GFC was the most important event that influenced the Indian economy through trade and finance channels. The global economic slowdown too dampened India's export demand and slowed its investment activity (Raj *et al.*, 2018). Finally, the global economy, including India, has also been severely impacted by the outbreak of the COVID-19 pandemic in 2020.

VI.3. Causal Linkages between Cycles

In order to gauge the interdependence between various macroeconomic cycles, the causal links between credit, investment and GDP cycles have been empirically estimated. In this context, three hypotheses *viz.,* (i) credit leading to investment, (ii) credit leading to GDP, and (iii) investment leading to GDP have been tested using the Granger causality test. The Granger causality test results are presented in Table 4.

As regards the first hypothesis, there was a bidirectional causal relationship between credit and investment in the pre-reforms period for the short cycles, while a bidirectional causal relationship existed in the post-reforms period for the medium cycles. Insofar as the second hypothesis of credit leading to GDP is concerned, a bidirectional causal relationship was seen for the medium cycle. Here, GDP and credit formed a feedback loop with a mutually reinforcing relationship. However, for the short cycle, we observed a unidirectional causality from GDP to credit, which implied that credit demand was higher when the economy performed well. While testing the third

Table 4: Granger Causality Test Results

Hypothesis	**Pre-1991**		**Post-1991**	
	F-statistics	**Prob.**	**F-statistics**	**Prob.**
Short Cycle				
Credit does not cause investment	20.33	0.00***	0.38	0.68
Investment does not cause credit	5.86	0.01***	0.85	0.44
Credit does not cause GDP	0.81	0.45	0.32	0.72
GDP does not cause Credit	2.75	0.07*	2.30	0.06*
Investment does not cause GDP	0.79	0.45	0.22	0.80
GDP does not cause investment	1.29	0.28	2.56	0.09*
Medium Cycle				
Credit does not cause investment	4.78	0.01***	6.48	0.00***
Investment does not cause credit	0.65	0.57	47.22	0.00***
Credit does not cause GDP	5.16	0.01***	6.06	0.01***
GDP does not cause Credit	13.77	0.00***	8.83	0.00***
Investment does not cause GDP	9.03	0.00***	14.67	0.00***
GDP does not cause investment	13.75	0.00***	6.45	0.01***

Note: lag of 2 was selected based on lag selection criteria for testing Granger causality.
*** : significant at 1 per cent and * : significant at 10 per cent.
Source: Authors' estimates.

hypothesis of investment leading to GDP, we observed a bidirectional causal relation in the medium cycle. Overall, the Granger causality test suggested that causal relations were stronger in the medium cycles than in short cycles.

VI.4. Synchronisation between Credit Cycles and Investment Cycles

Synchronisation measures the degree of co-movement of cycles. Based on the concordance index estimates, the paper found that the synchronisation between the credit cycle and investment cycle was around 66 per cent for the short cycle, while it was 65 per cent for the medium cycle (Table 5). This indicated that the two cycles moved in the same direction at the same time. This is also borne out by the Granger causality test, which suggested that both credit and investment had a bidirectional causal relationship in the medium cycle, particularly in the post-reforms period. Prolonged contraction in any of these cycles can have an adverse impact on economic growth.

As regards the synchronisation between credit and GDP cycles, it was about 70 per cent for short cycle and 58 per cent for the medium cycles. The degree of synchronisation was the highest (76 per cent) between investment and GDP in short cycle, though unidirectional causal relationship from GDP to investment was seen in the case of short cycle in the post-reforms period. However, in the medium cycle, both showed synchronisation of 68 per cent, with bidirectional causality.

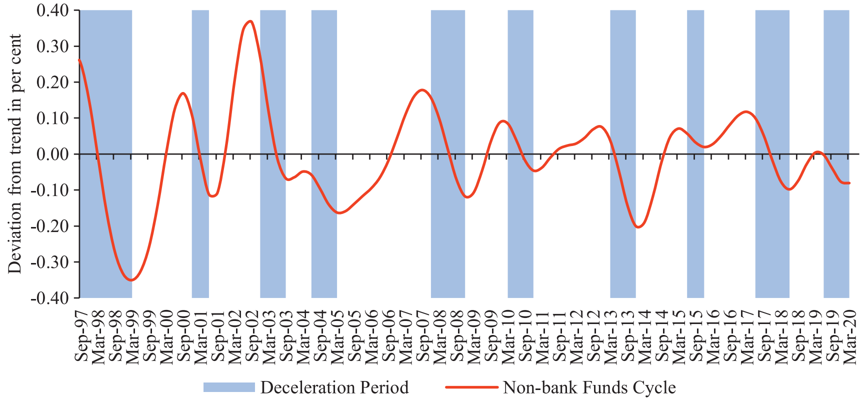
The results from the concordance indices were also corroborated by the contemporaneous correlation between credit cycles and GDP cycles where short cycles were more correlated than medium cycles. In general, based on the estimation, synchronisation between cycles was higher in the case of short cycles, while medium cycles exhibited a lower degree of synchronisation

Table 5: Concordance Index- Phase Synchronisation between Cycles

		Bank credit	Investment	GDP	
Short Cycle	Bank credit		0.65	0.58	Medium Cycle
	Investment	0.66		0.68	
	GDP	0.70	0.76		

Note: Figures in the lower triangle represent short cycle synchronisation and upper triangle represents medium cycle synchronisation.
Source: Authors' estimates.

Chart 4: Non-Bank Funding Cycle



Source: Authors' estimates.

because medium financial cycles have a much longer duration than business cycles, as discussed earlier.

VI.5. Non-bank Funding Cycle

An attempt was made to examine the cyclical characteristics of the non-bank funding cycle and its synchronisation with the bank credit, investment and business cycles. The non-bank funding cycle was extracted using CF filter and the cyclical pattern is presented in Chart 4. The estimated turning points are given in Annex Table A7.

Non-bank funding cycle phases were compared with bank credit cycles, investment and GDP cycles based on the quarterly data. If we look at the phase synchronisation of the non-bank funding cycle with other cycles, *viz.,* investment and business cycle, the degree of co-movement with investment and business cycles was not of the same level as compared with the bank credit cycle. The values of concordance indices estimated for the full period data, *i.e.*, from 1997-98: Q1 to 2019-20: Q4 are in Table 6. The phase synchronisation between the non-bank funding cycle and investment cycle was around 41 per cent, much lower than synchronisation with the bank credit cycle (61 per cent).

The synchronisation between non-bank funding cycle and the business cycle was also lower (48 per cent) than that with bank credit. This finding indicates that bank credit is still a prominent source of finance, which leads

Table 6: Phase Synchronisation

	Bank Credit Cycle	Non-Bank Funding Cycle	Investment Cycle	Business Cycle
Bank Credit Cycle	1	0.58	0.61	0.57
Non-Bank funding Cycle	0.58	1	0.41	0.48
Investment Cycle	0.61	0.41	1	0.83
Business Cycle	0.57	0.48	0.83	1

Note: Concordance Index (CI) has been used to measure the degree of phase synchronisation between cycles. The values of the CI range from 0 to 1. 1 means perfect alignment and 0 means perfect misalignment between phases.
Source: Authors' estimates.

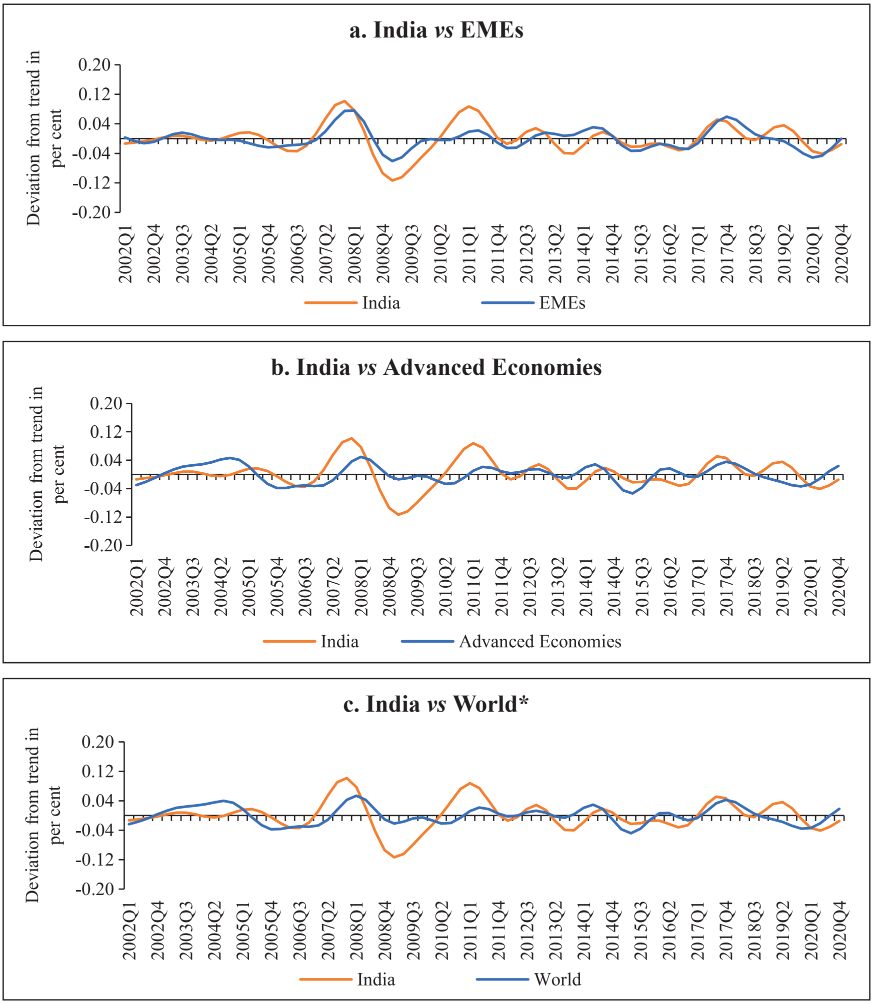
to greater investment and GDP in the economy. In the recent period, a major share of FDI inflows into India has taken place in the services sector, which limits investment in fixed assets. Also, as far as the end-use of ECBs is concerned, only a small portion goes to capacity addition or investments in plants and machinery. Thus, non-bank funds still play a limited role in financing investments in fixed assets as compared to bank credit.

VI.6. Synchronisation with Global Cycles

The features of credit cycle in the EMEs are different from that in the AEs. For EMEs, credit cycle is important given the dominance of the banking sector and its role in ensuring sustainable growth (Verma and Sengupta, 2021). As noted by Claessens (2011), the overall downturn of the financial cycle in the EMEs is more intense than in the AEs. In the case of the credit cycle, a downturn in the AEs is only one-third as deep as in the EMEs. In a similar fashion, business cycle in EMEs is more volatile than in the AEs. Possible causes for more intense cycles in EMEs could be that emerging markets, unlike developed markets, are characterised by frequent regime switches, and the dramatic reversals in fiscal, monetary, and other economic policies (Aguiar and Gopinath, 2007).

The phase synchronisation of the Indian credit cycle with that of the EMEs, AEs, and the world has been empirically estimated using quarterly data for the period 2002:Q1 to 2020:Q4. The estimated cycles are presented in Chart 5.

Chart 5: Bank Credit Cycle: India *vs* Other Major Groups of Countries



Note: (i) Data is for the period 2002-03 Q1 to 2020-21 Q4.
(ii) Cyclical component is extracted using CF filter following growth cycle approach.
(iii) * includes all countries reporting to Bank for International Settlements (BIS).

Sources: BIS; and Authors' estimates.

The synchronisation of the Indian credit cycle with the AEs' credit cycle has increased to 76 per cent in the post-GFC period from 64 per cent in the pre-GFC period (Table 7). A similar pattern has been observed in respect of synchronisation between credit cycles of India and EMEs; it increased to around 86 per cent in the post-GFC period from 61 per cent before the GFC.

Table 7: Credit Cycle Synchronisation- India *vs* External

Credit Cycles	Pre-GFC	Post-GFC	Full period
India- AEs	0.64	0.76	0.68
India- EMEs	0.61	0.86	0.72
India- World*	0.64	0.81	0.70

Note: Concordance Index (CI) has been used to measure the degree of phase synchronisation between cycles. The values of the CI range from 0 to 1. 1 means perfect alignment and 0 means perfect misalignment between phases. * includes all countries reporting to BIS.
Sources: BIS; and Authors' estimates**.**

For the full sample period, there is a greater synchronisation between credit cycles of India and EMEs than that with AEs, indicating a close relationship between the credit market developments among the EMEs. There is an increase in the synchronisation between the Indian credit cycles and external credit cycles in the post-GFC period, indicating greater integration of the Indian credit market with global credit markets.

Section VII
Conclusions

This paper analyses the dynamic interaction between credit, investment and business cycles in India based on data from 1950-51 to 2020-21. It also examines the degree of synchronisation of the Indian credit cycle with those of EMEs and AEs.

Based on an analysis of the medium duration cycles, the paper finds that the average duration of both expansionary and contractionary phases of the credit cycle in India is longer than that of the business cycle. In the expansionary phase of the credit cycle, the duration varies between 5 and 10 years, while in the contractionary phase, it varies between 3 and 14 years. The duration of the business cycle varied between 3 to 6 years and 3 to 7 years in the expansionary and contractionary phases, respectively. The duration of a contractionary phase of the credit cycle (11 years) was more prolonged than the expansionary phase (7 years).

Based on the Granger causality test, this paper finds evidence of bidirectional causal relationship between credit and investment cycles in the post-reforms period. This indicates the presence of a feedback loop between the financial sector and the real sector with both mutually interacting with and reinforcing each other. Further, the paper also observes a bidirectional causal relationship between medium duration credit and business cycles. The Granger causality test also established bidirectional investment - GDP causality. The causal relationships were much stronger in the case of medium cycles than short cycles.

The paper also investigates the degree of synchronisation of phases of cycles using a concordance index. The synchronisation between credit and investment cycle was around 66 per cent for the short cycle and 65 per cent for the medium cycle. A lower synchronisation was also seen between the medium duration credit and GDP cycles. These results suggest that the degree of co-movement of cycles is generally higher for short cycles.

Furthermore, the existence of causal relationships in the case of short cycles in the post-reforms period indicates that the impact of a contraction in any of the two cycles of varying duration can get amplified. This has to be controlled through effective policy measures. An early recognition of cyclical patterns can help in devising appropriate counter-cyclical stabilisation policies.

The paper estimates that the degree of synchronisation of non-bank funding cycle with business cycle is lower than of the latter with the bank credit cycle. This indicated that bank credit is still a predominant source of finance for investment in India.

The paper observes a higher degree of synchronisation of the Indian credit cycle with those in EMEs than in AEs. In general, the paper notes an increase in the degree of synchronisation between the Indian and external credit cycles in the post-GFC period, indicating the impact of greater integration of the Indian credit market with global finance.

The identification of the cyclical patterns in a timely and efficient manner is a useful tool for economic forecasting, which can be used for devising appropriate policies to smooth out the cycles. Effective counter-cyclical economic policy measures are required to address protracted cyclical deviations. Lessons learnt from the past crises point towards the need for policy makers to be more prudent during upswings and create adequate precautionary buffers to address large adverse shocks in the future.

References

Acharya, S. (2002). India: Crisis, reforms and growth in the nineties. Stanford Center for Research on Economic Development and Policy Reform, *Working Paper, 139*.

Aguiar, M. and Gopinath. G. (2007). Emerging Market Business Cycles: The Cycle is the Trend. *Journal of Political Economy* 115 (1): 69-102.

Aikman, D., Haldane, A., Nelson, B. (2015). Curbing the credit cycle. *Economics Journal*,125(585), pp.1072–1109.

Ariccia,D. G., Igan, D., Laeven, L., Tong, H., Bakker, B. & Vandenbussche, J. (2012). Policies for Macrofinancial Stability: How to Deal with Credit Booms,". International Monetary Fund (IMF). SDN/12/06.

Banerjee, K. (2011). Credit and Growth Cycles in India: An Empirical Assessment of the Lead and Lag Behaviour, *RBI Working Paper*, WPS No.22, December.

Bats, J.V. and A.C.F.J. Houben. (2017). Bank-based versus market-based financing: implications for systemic risk, *DNB Working Paper*, 577.

Behera, H. and Sharma, S. (2019). Does Financial Cycle Exist in India? *RBI Working Paper*, WPS N0.03, July.

Bjornland, H. (2000). Detrending methods and stylized facts of business cycles in Norway – an international comparison*, Empirical Economics*, 25(3).

Borio, C. Disyatat, P., Juseliu, M. and Rungcharoenkitkul, P. (2018). Monetary policy in the grip of a pincer movements, *BIS Working Papers*, no 706, March.

Brauning, F and Ivashina, V. (2019). U.S. monetary policy and emerging market credit cycles, *Journal of Monetary Economics*, https://doi.org/10.1016/j.jmoneco.2019.02.005

Bry, G. and Boschan, C. (1971). Cyclical analysis of time series: selected procedures and computer programs, *Technical Paper*, National Bureau of Economic Research, available at: www.nber.org/chapters/c2145

Burns, A., Mitchell, W. C. (1946). Measuring Business Cycles (Vol. 2). New York, NY: National Bureau of Economic Research.

Cecchetti, S. & E. Kharroubi. (2012). Reassessing the Impact of Finance on Growth *BIS Working Paper*, no 381.

Chauvet, M. (1998). An econometric characterization of business cycle dynamics with factor structure and regime switching. *International Economic Review*, 39 (4), pp. 969-96.

Chauvet, M. and Hamilton, J.D. (2006). Dating business cycle turning points, *Contributions to Economic Analysis*, 276, pp.1-54.

Christiano, L., Fitzgerald, T., (2003). The band pass filter, *International Economic Review*, 44 (2), pp. 435–465.

Claessens, S., Kose, M.A., Terrones, M.E. (2011). Financial Cycles: What? How? When?, *IMF Working Paper*, WP/11/76.

Claessens, S., Kose, M. A., & Terrones, M. E. (2012). How do business and financial cycles interact?. *Journal of International economics*, 87(1), 178-190.

Cumming, D., Zhang, Y. (2016). Alternative investments in emerging markets: A review and new trends', *Emerging Markets Review*. 29(C), pp. 1-23.

Drehmann, M., Borio, C. E., & Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: the role of credit aggregates.

Drehmann, M., Borio, C., Tsatsaronis, K. (2012). Characterizing the financial cycle: don't lose sight of the medium term, *BIS Working Papers*, No. 380.

Dua, P. and Banerji, A. (2006). Business cycles in India, Working Paper 146, Centre for Development Economics Department of Economics, Delhi School of Economics, available at: www.cdedse.org/pdf/work146.pdf

Dua, P. and Banerji, A. (2012). Business and growth rate cycles in India, Working Papers 210, Centre for Development Economics, Delhi School of Economics, available at: https://ideas.repec.org/p/cde/cdewps/210.html

ESRB, (2016). Macroprudential policy beyond banking: an ESRB strategy paper, European Systemic Risk Board, Frankfurt.

Gambacorta, L., J. Yang, and K. Tsatsaronis. (2014). Financial structure and growth, *BIS Quarterly Review*, pp.21-35.

Ghate, C., Pandey, R. and Patnaik, I. (2013). Has India emerged? Business cycle stylized facts from a transitioning economy, *Structural Change and Economic Dynamics*, 24, pp. 157-172, available at: https://ideas.repec.org/a/eee/streco/v24y2013icp157-172.html

Gomez-Gonzales, J.E., Ojeda, J., Tenjo-Galarza, F., Zarate, H.M. (2014). Testing for causality between credit and real business cycle in the frequency domain: an illustration. *Applied Economics Letters*, 21 (10), pp.697–701.

Haavio, M. (2012). Financial Cycles and Business Cycles: Some Stylized Facts. Bank of Finland.

Haavio, M., Mendicino, C., Punzi, M.T. (2013). Financial and economic downturns in OECD countries, Financial and economic downturns in OECD countries, Bank of Finland. *Research Discussion Papers,* 35/2013.

Hamilton, J. (2016). Why you should never use the Hodrick-Prescott filter, *Working Paper*, University of California.

Hamilton, J.D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica*, 57(2), pp.357-384, available at: www.jstor.org/stable/1912559

Harding, D. and Pagan, A. (2002). Dissecting the cycle: a methodological investigation 1, *Journal of Monetary Economics*, 49(2), pp.365-381.

Hieberta, P., Jaccardb, I., Schulerc, Y. (2018). Contrasting financial and business cycles: Stylized facts and candidate explanations, *Journal of Financial Stability*, 38, pp:72–80.

IMF (2015). The asset management industry and financial stability, *Global Financial Stability Report*, Chapter 3, Washington.

IMF (2008). World Economic Outlook, April 2008: Housing and the Business Cycle. International Monetary Fund.

Kemp, Esti, Renevan Stralen, Alexandros P. Vardoulakis, and Peter Wierts. (2018). The Non-Bank Credit Cycle, Finance and Economics Discussion Series 2018-076. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.076

Kent, C., & D'Arcy, P. (2001). Cyclical prudence-credit cycles in Australia. *BIS papers*, 1(2), 58-90.

Kitchin, Joseph. (1923). Cycles and Trends in Economic Factors, Review of Economics and Statistics, 5 (1), 10–16. doi:10.2307/1927031. JSTOR 1927031

Korotayev, Andrey. V., Tsirel, Sergey. V. (2010). A Spectral Analysis of World GDP Dynamics: Kondratieff Waves, Kuznets Swings, Juglar and Kitchin Cycles in Global Economic Development, and the 2008–2009 Economic Crisis, Structure and Dynamics, 4 (1), pp. 3–57.

Kumar, P., Senapati, M., and Prakash, A. (2021). Changes in Sectoral Bank Credit Allocation: Developments Since 2007-08, *RBI Monthly Bulletin,* September.

Law, S. H., & Singh, N. (2014). Does too much finance harm economic growth?. *Journal of Banking and Finance*, 41, 36-44.

Lee, M. W. (1955). Economic fluctuations. Homewood, IL, Richard D. Irwin.

Mall, O. P. (1999). Composite index of leading indicators for business cycles in India, *RBI Occasional Papers*, 20 (3), pp. 373-414.

Mendoza, E. G., & Terrones, M. E. (2008). An anatomy of credit booms: evidence from macro aggregates and micro data (No. w14049). National Bureau of Economic Research.

Minsky, H.P. (1964). Longer waves in financial relations: financial factors in the more severe depressions*, American Economic Review*, 54 (3).

Mohanty, J., Singh, B. and Jain, R. (2003). Business cycles and leading indicators of industrial activity in India", *MPRA Paper*, University Library of Munich, available at: http://EconPapers.repec.org

Pandey, R., Patnaik, I., Shah, A. (2017). Dating business cycles in India, *Indian Growth and Development Review*, 10 (1), pp.32-61, https://doi.org/10.1108/IGDR-02-2017-0013

Patnaik, I. and Sharma, R. (2002). Business cycles in the Indian economy, *Margin*- New Delhi-, 35, 71–80. ISSN 0025-2921.Pearson Prentice Hall.

Pontines, V. (2017). The financial cycles in four East Asian economies, *Economic Modelling*, 65, pp.51–66.

Raj, J., Sahoo, S. and Shiv Shankar. (2018). India's Investment Cycle: An Empirical Investigation, *RBI working paper*, WPS(DEPR) N0.05, October.

Rath, D. P., Kumar, S. (2021). Reassessing Investment Dynamics – Newer Insights into Leverage and Investment of the Indian Corporate Sector, *RBI working paper*, WPS(DEPR) N0.05, December.

Runstler, G. and Vlekke, M. (2017). Business, housing, and credit cycles. *Journal of Applied Econometrics*, 33(2), 212-226.

Samantaraya, A. (2007). An empirical analysis of pro-cyclicality of bank credit in India: Role of Basel prudential norms. In 43rd Annual Conference of the Indian Econometric Society.

Schumpeter, J. A. (1954). History of Economic Analysis. London: George Allen and Unwin

Strohsal, T., Proano, C. R., Wolters, J. (2015). Characterizing the financial cycle: Evidence from a frequency domain analysis. Discussion Papers 22/2015, Deutsche Bundesbank.

Sullivan, A. and Sheffrin, S. M. (2006). Economics: Principles in action.

Tinbergen, J. (1939). Statistical Testing of Business Cycle Theories: Part I: A Method and Its Application to Investment Activity. Agaton Press, Working Papers, No 352.

Verma, A. K., & Sengupta, R. (2021). Interlinkages between external debt financing, credit cycles and output fluctuations in emerging market economies. *Review of World Economics*, 157(4), 965-1001.

World Bank. (2007). Globalization of Corporate Finance in Developing Countries, Global Development Finance, World Bank, Washington, DC.

Zarnowitz, V. and Ozyildirim, A. (2002). Time series decomposition and measurement of business cycles, trends and growth cycles, *NBER Working paper*.

Annex

A1: Bry- Boschan (NBER) Business Cycle Dating Algorithm modified by Harding and Pagan (2002)

The Bry-Boschan (BB) and Harding Pagan (H-P) algorithms for estimating the turning points of a cycle are as follows:

1. The first step is the identification of the turning points *i.e.,* local minima (troughs) and local maxima (peaks) in a given time series.
2. Then ordering the troughs and the peaks *i.e.*, a peak is followed by a trough and a trough by a peak.
3. Checking pre-determined criteria of the duration and amplitudes of phases after steps 1 and 2.
4. Ensuring minimum duration and full length of a cycle - downturns and upturns have to be to be qualified as cycle phases, *i.e.,* each phase should have a duration of at least six months or two quarters for monthly / quarterly data.
5. For a time series $Y_{t-k}, \dots, Y_{t-k+1} < Y_t > Y_{t+1,\dots,} Y_{t+k}$, if a peak is at t, *k* needs to be set/ specified. As a convention, for monthly data, *k* = 5; for quarterly data *k* = 2 and *k* = 1 for annual data, where *k* is called the symmetric window parameter.
6. Two quarters for expansions and two contractions are generally applied for a minimum cycle, in line with NBER dating procedure. A complete cycle length (contraction plus expansion duration) of five quarters is also common for minimum cycle length as far as quarterly data is concerned. However, sometimes overrule the minimum restrictions.
7. Turning points are normally avoided at extreme points.

A2: Christiano – Fitzgerald (CF) Filter

Following the notations used in this paper, y_t is the cyclical components extracted from the timeseries y_t. The time series is assumed to follow a random walk without drift. Moreover, CF filter assigns different weights to each observation and hence the filter is asymmetric.

The extraction of cyclical components from the CF filter is calculated as follows:

$$y_t = B_0 x_t + B_1 x_{t+1} + \cdots + B_{\tilde{T}-1} x_T + B_1 x_{t-1} + \cdots + B_{t-2} x_2 + B_{\tilde{t}-1} x_1$$

where $B_j = \frac{\sin(jb) - \sin(ja)}{\pi j}$, $j \geq 1$, and = $B_0 = \frac{b-a}{\pi}, a = \frac{2\pi}{p_u}, b = \frac{2\pi}{p_k}$

$$\tilde{B}_l = -\frac{1}{2} B_0 - \sum_{i-1}^{l-1} B_j$$

where, p_u and p_k are the cut-off cycle length, which are 6 and 32 quarters, respectively, for quarterly data and 2 and 8 years for annual data. The cut-off points beyond 8 years, *i.e.*, 8-30 years are referred to as a medium cycle. Typically, cycle estimation considers 2-8 years in the Indian context, which is the convention in literature.

Table A3: Data and Sources

S. No.	Data/Variables	Period	Source
1	Non-food Credit	1950-51- 2020-21	DBIE, RBI
2	GDP	1950-51- 2020-21	DBIE, RBI
3	Gross fixed capital Formation (GFCF)	1950-51- 2020-21	DBIE, RBI
4	External Commercial Borrowings (ECBs)	1997:Q1-2019:Q4	DBIE, RBI
5	Funds mobilised from public issues	1997:Q1-2019:Q4	SEBI
6	Funds mobilised from private placements	1997:Q1-2019:Q4	SEBI
7	Gross fixed capital Formation (GFCF)	1997:Q1-2019:Q4	CSO, GoI
8	GDP	1997:Q1-2019:Q4	CSO, GoI
9	Foreign Direct Investment (FDI)	1997:Q1-2019:Q4	DIPP, GoI
10	Total credit-EMEs	2002:Q1-2020:Q4	BIS
11	Total credit-AEs	2002:Q1-2020:Q4	BIS
12	Total credit-world*	2002:Q1-2020:Q4	BIS
13	Total credit-India	2002:Q1-2020:Q4	BIS

Note: Public issue includes IPO, FPO and Rights issue; Private placement includes debt and equity. *Monthly values are averaged to make quarterly numbers.

Table A4: Descriptive Statistics of the Variables

	Bank Credit	GDP	Investment (GFCF)	Non-Bank Credit	ECBs	FDIs	Resources Raised from Primary Markets
Mean	15264.5	19049.8	5792.9	631.6	107.9	183.7	340.1
Median	13634.1	17123.3	5663.7	619.1	114.1	189.4	292.6
Maximum	36165.0	37095.1	11661.0	1765.3	303.0	489.6	1099.5
Minimum	2685.1	8046.2	1831.3	51.1	18.9	15.1	5.7
Std. Dev.	10603.0	8732.8	3021.1	461.5	61.1	138.5	285.9
Skewness	0.5	0.5	0.3	0.5	0.4	0.4	0.6
Kurtosis	1.9	2.0	1.8	2.2	2.8	2.0	2.5
Jarque-Bera	7.6	7.7	6.6	5.3	3.1	6.6	7.3
Probability	0.0	0.0	0.0	0.1	0.2	0.0	0.0
Observations	91	91	91	91	91	91	91

Source: Authors' estimates.

Table A5: Expansionary Phase (Annual Series)

Credit Cycle			Investment Cycle			Business Cycle		
Period	**Duration**	**Amplitude**	**Period**	**Duration**	**Amplitude**	**Period**	**Duration**	**Amplitude**
1952-53 to 1959-60	10	0.2	1953-54 to 1957-58	5	0.1	1957-58 to 1962-63	6	0.02
1974-75 to 1980-81	7	0.2	1960-61 to 1965-66	6	0.1	1967-68 to 1969-70	3	0.01
1984-85 to 1988-89	5	0.1	1975-76 to 1989-90	15	0.2	1976-77 to 1978-79	3	0.01
2001-02 to 2007-08	7	0.4	1995-96 to 1997-98	3	0.0	1983-84 to 1988-89	6	0.06
-	-		2003-04 to 2008-09	6	0.3	1994-95 to 1997-98	4	0.01
-	-		2014-15 to 2016-17	3	0.0	2003-04 to 2007-08	5	0.06
-	-		-	-		2012-13 to 2017-18	6	0.08
Average	**7***	**0.2**	**Average**	**6**	**0.1**	**Average**	**5**	**0.0**

Source: Authors' estimates.

Table A6: Contractionary Phase (Annual Series)

Credit Cycle			Investment Cycle			Business Cycle		
Period	**Duration**	**Amplitude**	**Period**	**Duration**	**Amplitude**	**Period**	**Duration**	**Amplitude**
1960-61 to 1973-74	14	0.22	1950-51 to 1952-53	3	0.06	1950-51 to 1956-57	7	0.01
1981-82 to 1983-84	3	0.02	1958-59 to 1959-60	2	0.01	1963-64 to 1966-67	4	0.01
1989-90 to 2000-01	12	0.34	1966-67 to 1974-75	9	0.20	1970-71 to 1975-76	6	0.03
2008-09 to 2020-21	13	0.36	1990-91 to 1994-95	5	0.11	1979-80 to 1982-83	4	0.01
-			1998-99 to 2002-03	5	0.14	1989-90 to 1993-94	5	0.04
-			2009-10 to 2013-14	5	0.08	1998-99 to 2002-03	5	0.06
-			2017-18 to 2020-21	4	0.07	2008-09 to 2011-12	4	0.03
						2018-19 to 2020-21	3	0.07
Average	**11***	**0.2**	**Average**	**5**	**0.1**	**Average**	**5**	**0.0**

Note: * End point is also considered for the calculation of duration as the deceleration period was too long.

Source: Authors' estimates.

Table A7: Estimated Turning Points of Cycles

Bank Credit Cycle		Non-Bank Funding Cycle		Investment Cycle		Business Cycles	
Peaks	**Troughs**	**Peaks**	**Troughs**	**Peaks**	**Troughs**	**Peaks**	**Troughs**
2000Q2	1998Q4	2000Q3	1998Q3	1999Q3	1998Q2	1999Q4	1998Q4
2002Q2	2001Q1	2002Q2	2001Q1	2001Q4	2000Q4	2001Q3	2000Q4
2005Q4	2004Q3	2007Q2	2005Q3	2004Q4	2002Q3	2003Q4	2002Q3
2007Q1	2006Q2	2009Q3	2008Q3	2007Q4	2005Q4	2007Q3	2005Q3
2008Q4	2007Q4	2012Q3	2010Q3	2011Q4	2009Q1	2011Q1	2008Q4
2010Q4	2009Q3	2014Q4	2013Q4	2016Q1	2015Q1	2014Q1	2013Q3
2015Q3	2014Q2	2016Q4	2015Q3	2018Q2	2016Q4	2016Q1	2015Q1
2019Q1	2017Q4	2019Q1	2018Q1			2018Q1	2016Q4

Note: Cyclical components are extracted using CF filter following growth cycle approach. Durations and amplitudes are estimated using the NEBR dating procedure.
Source: Authors' estimates.

Reserve Bank of India Occasional Papers
Vol. 43, No. 1: 2022

In Defense of Public Debt by Barry Eichengreen, Asmaa El-Ganainy, Rui Esteves, and Kris James Mitchener, 320 pp, Oxford University Press (2021), £22.99

Since the Global Financial Crisis of 2008, the domain of Economics has been enriched by the blending of other disciplines like Sociology and Psychology. Economic history is also making a comeback, as its insights are increasingly being used for a nuanced understanding of the current economic developments.

History helps us to situate the current economic issues and associated ambiguities in a context. In fact, Robert Solow has pointed out that, "the proper choice of a model depends on its institutional context" (Solow 1985, p. 329). The idea of "ubiquitous path dependency" of economic variables, which means that where we go next depends not only on where we are now, but also upon where we have been, has gained traction through the works of economists like Douglass North and Paul David.

Against this backdrop, the book under review titled "In Defense of Public Debt" offers a comprehensive historical account of public debt. It narrates the episodes of the debt crisis and debt consolidation, which help us to understand the context in which the current ideas on debt management have evolved.

The fiscal stimulus following the Global Financial Crisis reignited the debate on sustainable level of debt, austerity, and debt consolidation. The austerity debate was polarising in nature, peppered by the Rogoff-Reinhart's "Growth in time of Debt" paper which propounded the 90 per cent debt threshold hypothesis. This viewpoint was also shared by unconventional macroeconomic theories like the Modern Monetary Theory (MMT) that prescribed more radical views on government expenditure and debt financing.

The ongoing COVID-19 pandemic has seen an unprecedented support offered by governments across the world, resulting in almost an explosion of public debt. All these global developments of the recent past make this book a timely read, contributing richly to the spirited discussion on debt consolidation.

The book gives a chronological account of the evolution of public debt from early city states of Greece to the Global Financial Crisis and the ongoing pandemic. It traces the key role of public debt in imparting legitimacy to the state. Although public debt's origin can be traced back to 4th century BC, it was during the 10th century to 14th century that it evolved as an instrument of state financing.

The European states, geographically divided into smaller entities, forced to fight each other, resorted to debt funding of wars. The financial innovations like giving creditors representation in the assemblies, earmarking of revenues to debt servicing, and creation of long-term debt instruments which may be traded in secondary markets happened in the Italian city states out of the necessity to fund wars.

Political consolidation during the Middle Ages resulted in city states paving the way for nation states and larger entities. The evolution of larger political entities and complex political systems led to diverse experiments involving public debt. Some countries established institutions that reduced the sovereign's discretionary spending power and laws that could procure debt at lower costs.

Britain, especially after the Glorious Revolution of 1688, provided an example of institutional support for sustainable public debt management. Constitutional monarchy and stability helped Britain to borrow at lower costs. Constitutional monarchy implied the rule of law, which ensured that the parties adhered to contractual obligations that led to the development of secondary markets and ease of access to raise public debt. On the contrary, Spain and France failed to pursue political reforms, which limited the sovereign's ability to borrow. The lack of reforms, thus, increased their borrowing costs.

As nation states crystallised, public debt was used to finance the growing needs of the states. Public debt also gave legitimacy to the state, and enabled it to meet the public needs, including sewage system, water and transport systems, and other public infrastructure involving high upfront costs and social returns spread over a longer horizon.

The 18th and 19th centuries were the age of Industrial Revolution, colonialism and increasing foreign trade. The book elaborates on three episodes of successful debt consolidation during the 19th century, primarily through budget surpluses and economic growth: Britain after the French and Napoleonic Wars, the United States after the Civil War, and France after the Franco-Prussian War. This was possible as Industrial Revolution led to productivity gains along with rising colonial power and a prudent state, reducing the demands on state's exchequer.

The dawn of the 20th century led to the birth of the welfare state. This further led to the burgeoning of public debt along with the First World War. The book elaborates in detail the consolidation of debts during the inter-War years and the different approaches to debt consolidation.

Debt reduction was achieved, in roughly equal measure, by running primary budget surpluses and maintaining a favorable differential between growth rate and interest rates. The 1920s showed how high debt can be reduced. Britain and France reduced debt by maintaining consistent primary surpluses. In Italy, forced conversion of short-term debt to long term debt by Mussolini led to reduced interest rates which had a positive impact on the differential between growth rate and interest rates. In Germany, hyperinflation liquidated the debt. Welfare expenditure and war reparations were financed by the monetisation of debt.

Central bank's influence on public debt management became more prominent during the Second World War and the following three decades during which central banks administered rate ceilings on Treasury Bills along with huge bond purchases. The Bank of England, by the end of the War, had an extraordinary 98 per cent of its assets in the form of government securities.

The main factor helping debt consolidation during this period was the interest-growth differential. Low interest rates due to financial repression, low real interests due to inflation and high growth due to post-War reconstruction had a positive impact on public debt. Primary balances also contributed in a minor way. High growth generated enough revenues to support the social security payments.

Before the Global Financial Crisis, several emerging market economies, including Mexico, Brazil, Argentina, South Korea, Thailand and Turkey experienced serious debt-servicing problems. The book draws certain lessons from emerging market debt servicing problems during the 1980s and 1990s. First, funding fiscal deficits with short-term debt is risky because the demand for debt securities can dry up abruptly. Second, foreign-currency debt may be risky, since the sovereign's debt-servicing capacity will depend on its ability to generate foreign exchange receipts, which can fluctuate for reasons beyond its control. Thirdly, governments should foster local markets in long-term debt securities. Finally, fiscal dominance can jeopardise banking sector stability. To illustrate, when the bond market is underdeveloped and borrowing is costly, policy makers may direct bank investments into government bonds. Thus, a fall in the prices of those bonds can affect treasury earnings, and thereby banking sector stability. The lesson, therefore, is to avoid this temptation.

The authors also underline the need for central banks to create backstops for the debt market. With volatility in the macroeconomic and financial environment, the debt-to-GDP ratio or the economic growth–interest rate differential can move in an unfavorable direction. It can also be triggered by a simple loss of confidence, as happened in France in the 1920s and Asia in the 1990s. The rollover of debt may become difficult in such situations, leading to panic among investors. In such situations, the central bank has to act as the liquidity provider and bond buyer of last resort. Towards this, the authors cite the 2012 pledge by Mario Draghi to "do whatever it takes" to prevent debt runs in the Euro Zone as a case in point. The mere expression of intention and announcement of the ECB's readiness to backstop the markets was enough to stabilise prices.

Finally, the authors discuss the tsunami of public debts issued after the COVID-19 pandemic, pointing that countries with fiscal space could give higher support than countries with limited space. The pandemic brought to fore the need to build up fiscal space during good times through prudent debt consolidation to realise the full potential of public debt. It once again underlined the role of central banks as liquidity providers of the last resort.

While the book acknowledges the dangers of misuse and excessive dependence on public debt, it does not delve into details. The book is commendable for its craft in blending history with the contemporary insights on public debt. However, detailed narration of events where public debt failures led to problems like increased debt servicing costs, higher interests along with runaway inflation would have added completeness to the discussions in the book.

The book is largely written from a developed countries' perspective except for a chapter on emerging markets' crisis of the 1990s. For example, colonialism which led the globalisation of financial capital in the 19th century has had a positive impact on public debt consolidation and growth in the developed countries. But the counter factual impact on the colonies was equally important for emerging economies' public debt experience in the later half of the 20th century. While the earlier half has been discussed in detail, the later half has been barely mentioned.

Overall, the book tries to counter the morality-based vilification of public debt by highlighting the positive ends at which public debt has been historically placed. The broad history of public debt shows that it has been the only anchor for the state during times of wars, pandemics and unexpected shocks. The historical episodes reviewed suggest that the heavy debts with which governments and societies emerge from events like wars, financial crises, and other emergencies are best stabilised through a combination of approaches: by running primary surpluses, tolerating moderate inflation, and encouraging economic growth. Shortcuts to consolidate debt like through higher inflation and fiscal dominance are unsustainable. This may be an important policy implication for a post-COVID public debt management in both developed and developing economies. Philosophically, the book appears to espouse Aristotle's virtue theory (in Nicomachean Ethics) for public debt and debt management - "Virtue is the golden mean between two vices, the one of excess and the other of deficiency."

Akash Kovuri*

---

* Akash Kovuri is Manager in Department of Economic and Policy Research at the Reserve Bank of India, Mumbai.

Reserve Bank of India Occasional Papers
Vol. 43, No. 1: 2022

Geopolitics, Supply Chains, and International Relations in East Asia Edited by Etel Solingen, University of California, Irvine, 350 pp, Cambridge University Press (2021), $34.99 (Paperback)

Last three decades have seen a progressive liberalisation of cross-border transactions following technological advancements, reliable and low-cost transportation and a benign trading environment. Cost reduction strategies have incentivised firms to unbundle the production processes geographically. This has created complex global supply chains (GSCs) or global value chains (GVCs) (global production networks, and international production networks) which account for about 70 per cent of international trade today (OECD, 2021). The successful implementation of policies favourable to GVCs by the East-Asian countries have led to faster growth, rise in productivity, job creation, higher living standards and technological upgradation. India's participation in GVCs, however, has been subdued as compared to its Asian peers, such as China, South Korea, Taiwan, Vietnam, Hong Kong and Malaysia.

In this context, the book under review titled "Geopolitics, Supply Chains, and International Relations in East Asia" offers interesting insights for India as it strives to move up in the GVC participation through proactive trade policies and business-friendly trade facilitation measures. In order to hasten India's participation in value-added trade, the Government of India introduced 'Make in India' and Production-Linked Incentive (PLI) schemes. Moreover, there has been a renewed focus on developing world-class logistics and port infrastructure. However, GSCs have witnessed a number of shocks in the recent times, including calls for more localised productions by advanced countries (including the US, Japan, the UK and the EU), disruptions caused by COVID-19, geopolitics and trade wars, climate risks and extreme weather events. These developments have underlined the need to further strengthen the policy support to GSCs.

The book dissects the sources and effects of contemporary disruptions of the global production networks. The editor of the book, Etel Solingen, brings together an interdisciplinary group of scholars to analyse GSCs in the context of both domestic, political and economic systems of various countries, and international cooperation and conflict. The volume presents GSCs as a unique but complex mechanism of interdependence to analyse the broader patterns in inter-state relations. The book focuses on the growing role of China and other East-Asian countries in GSCs and its implications for the global economy and international cooperation. It discusses how the East-Asian countries share a unique economic infrastructure that has resulted in the concentration of manufacturing in this region, creating what is often called as the "Factory Asia". Interestingly, the GSCs in these countries have been a result of the outward-oriented growth models implemented by these countries over the last five decades. However, the recent turn of events in the global order with calls for inward-orientation have exposed these GSCs and outward-oriented growth models to political and economic vulnerabilities.

The second chapter in the book written by Yuqing Xing offers a critique of conventional trade statistics that focus on bilateral trade to bring out the surplus or deficit of a country with its trade partner. A persistent US trade deficit with China triggered the trade war between the two largest economies. However, the author argues that such conventional bilateral trade statistics provide an incomplete view of international trade. He claims that the conventional trade statistics exaggerate Chinese trade surplus with the US, as the trade contains a large component of imported intermediates.

Also, current metrics assume that the entire value addition of Chinese exports is created in China, though China only assembles components imported from Japan, South Korea and other Asian economies, and exports them back to the US. Furthermore, the conventional trade statistics do not record the massive earnings of the multinational enterprises that have assumed the form of "factory-less" American manufacturers enjoying a monopoly over intellectual property rights. Their products sold to foreign consumers do not cross the US borders. Also, the value-added by intellectual property is embedded in physical goods. Owing to the aforementioned arguments, the author calls for reforming the current trade statistics for a better understanding of trade imbalances.

Chapter 3 by Hongyong Zhang in the book documents the impact of trade wars on Japanese firms. He observes that the efforts to "decouple" GSCs are resulting in policy uncertainty and increasing costs due to the imposition of additional tariffs, impacting trade and investment decisions by Japanese firms. This has led to reshoring decisions and redeployment of GSCs into the Association of South East Asian Nations (ASEAN). Evidently, the trade tensions between two trading partners can also impact other countries.

In Chapter 4, Victor Shih brings forth the role of government policies in shaping the Artificial Intelligence (AI) value chain industry. He discusses the interesting case of China's decision to control the entire AI supply chain within its national boundaries, placing a large part of the chain under the purview of its government to respond quickly in emergency situations.

Chapter 5 by Momoko Kawakami uses the example of the smartphone industry to highlight the complementary positions of the East-Asian countries in GSCs. The electronics hardware industry is driven by three major industry actors – lead firms, contract manufacturers and platform leaders. Powerful lead firms (from developed economies) set product strategy with the suppliers (from developing countries) by defining the product, production process and deciding the quantity of production.

In the smartphone industry, "platform leaders" are important players providing the highly integrated chips (semi-conductors). The author argues that the development of this industry has been path-dependent in South Korea, Taiwan and China even before the handset boom of the 1990s, although there have been differences in the industry organisations across these countries. The industrial development programmes strengthened the positions of the East-Asian economies in GSCs. Furthermore, competition and collaboration among the East-Asian firms resulted in East Asia taking a dominant position in the production network. The author argues that such high level of complementarity can help in imparting resilience to GSCs in East Asia in the face of growing political rivalries and diplomatic tensions.

In Chapter 6, Kristen Aanstoos proposes a theoretical framework to understand the effects of state actions and the international political environment on the geographical distribution of supply chains in East Asia. The author argues that the legal actions and imposition of trade barriers have increased costs and operational uncertainty in various nodes of GSCs, triggering two kinds of effects: “contractionary shifts” that reduce the overall number of nodes, and “diversionary shifts” that shift the nodes from one country to another.

Part II of the book looks at the domestic political, economic and social dimensions affecting GSC-related policies in various states. Chapter 8 by Nazim Uras Demir and Etel Solingen assesses whether GSC participation is vital to Chinese policymakers. China’s outward-oriented growth model has led to an expansion in its participation in western GSCs. This model has been portrayed as a success story by Chinese leaders. However, the Chinese GSC structure has thrown up challenges of sustainability, particularly in terms of employment generation.

In addition, China is facing external shocks of political backlash against offshoring in Western countries. These developments have led to disagreements relating to GSCs within China. Three groups with different opinions about the future of Western GSCs have been discussed in the chapter, “GSC preservers”, “GSC reformers” and “GSC replacers”. As a response to the trade war, the preservers view that China benefitted immensely from GSCs and it should not abandon them. Reformers call for rebalancing China’s participation in higher value-added sectors. Replacers, on the other hand, favour the substitution of western GSCs with those dominated by China.

In Chapter 9, authors Jieun Lee and Iain Osgood study the political activities of firms and industry associations in response to the US trade war. They find little organised support for a trade war against China among American producers. In contrast, they find robust and well-organised opposition to the tariffs imposed by the US. This shows that firms resisted policies that push reshoring and preferred existing production networks relying on imported inputs.

Pheobe W. Moon, in Chapter 11, develops a prospect theory to hypothesise a country’s response to geopolitical conflict. State’s perception of its relative position in GSCs explains its choice to de/escalate the conflict. When a state’s key industries are more dependent on the opponent within their shared GSCs, its leaders are more likely to escalate conflicts. This asymmetry in dependency makes policymakers see themselves in a strategically disadvantageous position, and the prospect of being replaced in the GSCs predisposes them towards more risk-seeking behaviour. By contrast, when a state holds relative dominance within the GSC, its leaders are less likely to risk conflict escalation.

In sum, this volume is an interesting read to understand the possible implications of geopolitical tensions for GSCs. The perception offered by the book on conventional trade statistics underlines how a deeper understanding of global value chains is necessary for formulating trade policies. The book reiterates how the trade tensions involving two nations impact not only the parties involved but also other countries having production facilities in either of these countries. It also brings out how government policies can alter the location of production chains. However, it is important to avoid firm domination, as seen in the Chinese AI industry.

In this context, the Government of India's push for "Make in India" and PLI scheme may play a significant role in enhancing domestic production in the years to come. India could benefit from positive spillovers from GSCs, including through technology upgradations. Furthermore, India's participation in buyer and producer-driven value chains can create a bridge for foreign consumers of Indian products.

Rashika Arora*

* Rashika Arora is Manager in Department of Economic and Policy Research at the Reserve Bank of India, Mumbai.

Reserve Bank of India Occasional Papers
Vol. 43, No. 1: 2022

Chain Reaction: How Blockchain Will Transform the Developing World by Paul Domjan, Gavin Serkin, Brandon Thomas and John Toshack, 114 pp, Palgrave Macmillan, Switzerland (2021), €24.6

Blockchain technology or distributed ledger technology (DLT) has a promising potential for propelling future innovation in different sectors. The discourse on blockchain technology and its applications often gets sidelined by cryptocurrencies. In this regard, this book on blockchain by four field experts is a useful read. Though the opinions expressed may seem debatable, the narrative of the book is lucid and comprehensible. Unlike other books on the same topic, this book abstracts itself from overly technical explanations, and tries to build on the potential of technology for developing nations. The book explores diverse applications of DLT and explains its status, working, issues and possible future course using case studies from different countries.

DLT refers to any networked system that facilitates expanding, chronologically-ordered list of immutable records, and allows all users within the system to verify the data. The premise of the book is that the problems in developing countries linked to trust, verification and value transfers can be solved using DLT. Thus, the value of blockchain solutions outweighs the value delivered by more traditional methods. The book draws parallels from mobile phones, which helped developing countries "leapfrog" the intermediate technology of communication used in advanced economies. The book is arranged as follows: after a short introduction, Chapter 2 explains the problem of trust, Chapter 3 tries to answer what blockchain solves and Chapter 4 goes on to discuss the technical details of blockchain and who controls it. Chapter 5 focuses on the money transfer solutions, and Chapters 6 and 7 talk about all other applications. The final chapter evaluates the future course of technology adoption.

The chapter on trust highlights the importance of trust in running the global economy. Reliance on intermediaries in property registration and credit rating helps banks in dealing with private mortgages and investors in buying stocks, respectively. Many developing countries lack such institutions of trust, as illustrated by the example of property registration frauds in Nigeria. The ease of enforcing contracts projected by the World Bank's Doing Business paints a similar picture.

The next chapter builds on the first one and explains that the objective of blockchain is to provide the confidence that the information is beyond any influence. Although verification related risks are reduced by DLT, other risks like forgetting one's key still exist. There is a possibility of taking greater risk in a secure environment or 'risk homeostasis'.

Chapter 4 spells out in brief the technical aspects of blockchain like users, nodes, miners, hashing and tokens. The authors take an example of a blockchain solution used by Walmart to improve its food supply visibility, which helped to track food items as well as identify contaminated food quickly. This showed that the DLT applications encompass various fields from legal to medical to foreign aid and make a case of blockchain being more than a technology, in fact, an infrastructure. The interaction of blockchain with the Internet of Things (IoT) and the issues of scalability and security are also discussed in the book.

Chapter 5 delves into the contentious topic of cryptocurrencies and compares them with physical cash and electronic cash on parameters of transactions, settlement, handling, storage, altering transaction and acceptance. The authors note the complications cryptocurrencies can pose to macro-stability, and yet choose an optimistic view on the subject.

In Chapter 6, crucial applications in the context of property registrations, foreign aid, health records, government identity, financial inclusion, voting, tax revenue and notarisation are discussed with examples. In the case of property registration, blockchain helps in providing the proof validation or provenance. Users can create a digital record of proof of transaction and upload the record. This hash, once appended to the blockchain, can create an immutable evidence. Such a system, according to the authors, could be transparently inspected or verified. Such formal and secure property rights can form the backbone for further development in an economy. While the advantages of using blockchain in creating secure property rights are well-appreciated, property registration systems are at various stages of development across countries and replacing such heterogenous systems without inheriting their errors is a major challenge. And hence, the authors themselves note that if an easier alternative is available to solve a given problem, it may be tried first instead of going for a purist concept of blockchain.

Following the estimate that about one-third of its budget goes to validate whether the aid is received by the intended recipient or not, the World Bank launched its Blockchain Lab in 2017 to assist in transparency and verification. Not just authentication but donor coordination can also be taken care of by using blockchain. A case study of Oxfam's project in Vanuatu illustrated in the book highlights how in addition to ensuring end-use, administrative tasks like accurate distribution and monitoring can be reduced using blockchain. Similarly, TruBudget, a system by KfW, which creates traceability on all activities related to each item of expenditure, has been made open-source and free to access by the German government. The system breaks each project into sub-projects and then into workflows. Each workflow has one assignee, who uploads the proof of completion of the task, which being immutable, holds him/her accountable.

There are multiple use cases of blockchain illustrated in the book. In the field of medical records, blockchain helps in creating secure audit trails of access to records and enables the patient or the regulator to check who views the report. From the perspective of financial inclusion, the Philippines' Union bank case study to enable rural unbanked sections to receive remittances more efficiently and safely is discussed. There is also a case for using DLT for innovative approaches to credit score. The book notes the role blockchain solutions can play in voting and identity. The most difficult problem, however, with regard to applications of DLT is to ensure the legitimacy of initial data entered – an intersection between humans and blockchain.

Counterfeit drugs are a rampant problem in the developing countries. The blockchain solution can help buyers to validate provenance using a unique QR code on the packaging. Any counterfeit QR code can lead to an enforcement action. To replicate this solution on a larger scale would require a public authority to create QR codes and greater international cooperation. Another popular use of blockchain is in the supply chain validation adopted by major tech firms. A case study in the book brings out how blockchain can help companies to tokenise the receivables and collateral with creditors, which ensures that the same invoice cannot be pledged multiple times. In the area of international trade, digitalised systems offer simplified trade documentation by creating timestamped historical records of each document, thereby allowing differential access rights. Adding digital currency, digital ports and smart contracts to the equation, can reduce dependence on trade credit insurance. The book argues that for South-South trade, where the normal trade credit route is not robust enough, such a solution can be utilised.

The last chapter evaluating the future course of technology adoption predicts two possible trajectories for this adoption, conditional on government reaction. In both scenarios, the usage of blockchain technology will continue to grow. However, the authors anticipate the technology to stay predominantly in the informal sector, with the government essentially being on the other side of the fence. The authors club all applications of blockchain, including cryptocurrencies, and expect a similar treatment for all applications from the government, which seems unlikely. For a more nuanced and academic discussion on this subject, the book "Blockchain and the Public Sector" can be considered for further reading. In this book, Sobolewski and Allessie investigate seven real-life blockchain deployments in the public sector in Europe and find that governmental experiments dealt with primarily three blockchain functionalilities *viz.,* notarisation, shared database and workflow automation. As per their analysis, current blockchain-driven innovations mainly consist of automating the enforcement of transactions and that the applications primarily seek to reduce bureaucracy and costs of administrative processes, like record-keeping.

Various applications of blockchain have been dissected primarily from the perspective of developing countries in the book. However, even if the book focuses on developing countries, it is still context specific and recommends that the adoption of blockchain will depend on the nature of prevailing institutions and technologies. This can also be observed from case studies. Thus, while Kenya benefitted greatly from money transfer solution, a company in Taiwan utilised blockchain technology to develop an application to help contain COVID-19.

Despite some of the omissions discussed in the foregoing paragraph, the book under review does justice to what it sets out to achieve. The authors take care to explain blockchain in a way that is intelligible to the uninitiated and offers sufficient depth to comprehend the issues involved in its implementation. As blockchain technology and its utilisation are evolving, it serves well to stay updated. The book under review is useful precisely for the same reason.

Anshu Kumari*

* Anshu Kumari is Manager in Department of Economic and Policy Research, Reserve Bank of India.

Regd. No.: “No. R. N. 37535/80”

Published by Pallavi Chavan for the Reserve Bank of India, Shahid Bhagat Singh Road, Fort, Mumbai - 400 001 and printed at ACME Packs & Prints (I) Pvt. Ltd., A Wing, Gala No.73, Virwani Industrial Estate, Goregaon (East), Mumbai - 400 063.